HEART FAILURE DISEASE PREDICTION USING ENHANCED MULTI-LAYER PERCEPTRON FRAMEWORKS

THESIS

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MALANG
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Submitted to:
State Islamic University Maulana Malik Ibrahim Malang,
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Dedication

To the soul of my beloved father, *may Allah have mercy on him*, who was always my source of inspiration and strength. I pray that this work adds to his good deeds.

To my dear mother, the symbol of love and sacrifice, whose prayers and unwavering support have been my greatest blessing.

To my cherished family, my brothers and sisters, who have always been my pillar of strength throughout my journey.

To my esteemed teachers, who have illuminated my path with knowledge and wisdom, dedicating their time and effort to guide me.

To my dear friends, who have stood by my side, sharing moments of hard work and perseverance, always offering encouragement and support.

To everyone who has contributed to my growth and success, I dedicate this work with heartfelt gratitude, hoping it will be of benefit and value.

Introduction

Bism Allah Alrahman Alrahimi.

Praise be to Allah, by whose grace all good deeds are completed, and by whose favor all goals are achieved. I offer my gratitude and praise to Him, as is befitting His Majesty and Greatness. May peace and blessings be upon our Prophet Muhammad, his family, and his companions.

This research aims to study *Heart Failure Disease*, recognizing the significant impact of this condition on patients and its association with sudden fatalities, Throughout the preparation of this work, I have received immense support and encouragement from numerous individuals who deserve my sincere gratitude and appreciation.

To the soul of my father, *Hamid Salih Hamid*, may *Allah have mercy on him*, who was always a source of inspiration and strength in my academic journey, constantly encouraging me to seek knowledge wherever it may be. I pray that this work adds to his good deeds and serves as an ongoing charity *sadaqah jariyah* for him. To my mother, who has been my pillar of support, always keeping me in her prayers and offering unwavering encouragement. To my esteemed teachers, who have generously shared their knowledge and guidance. To my colleagues and friends, and to everyone who has stood by my side throughout this journey, through both hardships and moments of joy, offering their sincere support and companionship.

I hope that this research will be beneficial and meaningful, and I pray that it serves as valuable knowledge.

Malang, 28 may 2025

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Terminology Table

Abbreviation	Term
MLP	Multi-Layer Perceptron
LSTM	Long Short-Term Memory
RNN	Recurrent Neural Network
GRU	Gated Recurrent Unit
RF	Random Forest
SVM	Support Vector Machine
KNN	K-Nearest Neighbors
DT	Decision Tree
NB	Naive Bayes
LR	Logistic Regression
PSO	Particle Swarm Optimization
Accuracy	The proportion of correct predictions out of all cases.
Precision	The proportion of true positive predictions out of all predicted positives.
Recall	The proportion of actual positives correctly identified.
F1-score	The harmonic means of precision and recall for balance.
ROC-AUC	Receiver Operating Characteristic - Area Under Curve
HER	Electronic Health Records

ABSTRAK

Penelitian ini bertujuan untuk membangun model prediktif untuk gagal jantung berdasarkan jaringan saraf multilayer perceptron (MLP), sekaligus meningkatkan kinerjanya dengan menggabungkan algoritma molecular swarm optimization (PSO). Deteksi dini gagal jantung sangat penting untuk mengurangi angka kematian, meningkatkan kualitas hidup pasien, dan mengurangi beban pada sistem perawatan kesehatan. Model ini diterapkan pada kumpulan data medis yang tersedia di platform Kaggle, yang berisi 918 catatan klinis yang mencakup 12 variabel kesehatan utama, seperti usia, tekanan darah, kolesterol, dan gula darah puasa.

Serangkaian eksperimen dilakukan menggunakan rasio split yang berbeda antara data pelatihan dan data uji, mulai dari 90:10 hingga 55:45, untuk memeriksa kinerja model dalam berbagai kondisi. Hasil penelitian menunjukkan bahwa model yang ditambah PSO berkinerja lebih baik daripada model dasar dalam semua skenario, mencapai akurasi tertinggi sebesar 92,39% pada rasio 90:10, sekaligus mempertahankan keunggulannya dalam presisi, recall, dan rasio F1. Bahkan dengan set data pelatihan yang diperkecil, model tersebut menunjukkan kemampuan generalisasi yang baik dan stabilitas yang luar biasa, yang menegaskan keefektifannya dalam memprediksi gagal jantung.

Hasil analisis juga menunjukkan bahwa faktor prediksi yang paling berpengaruh meliputi depresi segmen ST, tekanan darah saat istirahat, dan kadar kolesterol. Hasil ini menyoroti keefektifan model yang diusulkan sebagai alat bantu dalam diagnosis dini penyakit. Studi ini merekomendasikan perluasan ukuran set data, peningkatan kualitas fitur, pemanfaatan teknik pengoptimalan tingkat lanjut seperti PSO, dan pengintegrasian model dengan metode analisis yang lebih canggih untuk meningkatkan efisiensi dan akurasi. Studi ini menegaskan peran jaringan saraf yang semakin meningkat dalam bidang medis dan dampaknya dalam mendukung sistem diagnosis dini, mengurangi komplikasi penyakit, dan meningkatkan kualitas layanan kesehatan.

Kata kunci: Gagal jantung, pembelajaran mendalam, jaringan saraf multilapis (MLP), prediksi medis, penambangan data..

ABSTRACT

This research aims to build a predictive model for heart failure based on a multilayer perceptron (MLP) neural network, while improving its performance by incorporating the molecular swarm optimization (PSO) algorithm. Early detection of heart failure is crucial for reducing mortality rates, improving patient quality of life, and reducing the burden on healthcare systems. The model was applied to a medical dataset available on the Kaggle platform, containing 918 clinical records covering 12 key health variables, such as age, blood pressure, cholesterol, and fasting blood sugar.

A series of experiments were conducted using different split ratios between training and test data, ranging from 90:10 to 55:45, to examine the model's performance under various conditions. The results showed that the PSO-augmented model performed better than the baseline model in all scenarios, achieving the highest accuracy of 92.39% at the 90:10 ratio, while maintaining its superiority in precision, recall, and F1 rate. Even with a reduced training dataset, the model demonstrated good generalization ability and remarkable stability, confirming its effectiveness in predicting heart failure.

The analysis results also showed that the most influential predictive factors included ST-segment depression, resting blood pressure, and cholesterol levels. These results highlight the effectiveness of the proposed model as an aid in early diagnosis of the disease. The study recommends expanding the dataset size, improving feature quality, utilizing advanced optimization techniques such as PSO, and integrating the model with more sophisticated analysis methods to increase efficiency and accuracy. This study confirms the growing role of enhanced neural networks in the medical field and their impact on supporting early diagnosis systems, reducing disease complications, and improving the quality of healthcare services.

Keywords: Heart failure, deep learning, multilayer neural network (MLP), medical prediction, data mining.

الملخص:

يهدف هذا البحث إلى بناء نموذج تنبؤي لمرض قصور القلب بالاعتماد على الشبكة العصبية متعددة الطبقات(MLP) ، مع تحسين أدائها من خلال دمج خوارزمية تحسين السرب الجزيئي .(PSO) وتكمن أهمية الكشف المبكر عن قصور القلب في دوره الحيوي في خفض معدلات الوفيات، وتحسين حياة المرضى، وتقليل الضغط على نظم الرعاية الصحية. تم تطبيق النموذج على مجموعة بيانات طبية متاحة عبر منصة Kaggle، تحتوي على 918 سجلًا سريريًا تتضمن 12 متغيرًا صحيًا رئيسيًا، مثل العمر، ضغط الدم، الكوليسترول، وسكر الدم الصائم.

تم تنفيذ سلسلة من التجارب باستخدام نسب تقسيم مختلفة بين بيانات التدريب والاختبار، تراوحت من 90:10 إلى 55:45، بهدف دراسة أداء النموذج في ظروف متنوعة. وقد أظهرت النتائج أن النموذج المُعزز باستخدام PSO قدّم أداءً أفضل من النموذج الأساسي في كافة السيناريوهات، حيث سجّل أعلى دقة بلغت 92.39% عند نسبة 90:10، مع الحفاظ على تفوقه في مؤشرات الدقة(Precision) ، الاستدعاء(Recall) ، ومعدل .F1 حتى في حالات تقليل نسبة بيانات التدريب، أظهر النموذج قدرة جيدة على التعميم وثباتًا ملحوظًا، مما يؤكد كفاءته في التنبؤ بحالات قصور القلب.

كما بيّنت نتائج التحليل أن العوامل الأكثر تأثيرًا في التنبؤ تشمل اكتئاب مقطعST ، ضغط الدم أثناء الراحة، ومستوى الكوليسترول. تُبرز هذه النتائج فعالية النموذج المقترح كأداة مساعدة في التشخيص المبكر للمرض. وتوصي الدراسة بالتوسع في حجم البيانات المستخدمة، وتحسين جودة السمات، والاستفادة من تقنيات تحسين متقدمة مثلPSO ، إلى جانب دمج النموذج مع أساليب تحليل أكثر تطورًا لزيادة الكفاءة والدقة وتؤكد هذه الدراسة الدور المتنامي للشبكات العصبية المُحسّنة في المجال الطبي، وأثرها في دعم أنظمة التشخيص المبكر، والحد من مضاعفات الأمراض، والارتقاء بجودة خدمات الرعاية الصحية.

الكلمات المفتاحية :قصور القلب، التعلم العميق، الشبكة العصبية متعددة الطبقات(MLP) ، التنبؤ الطبي، التنقيب عن البيانات.

CHAPTER I

INTRODUCTION

1.1. Background.

Heart disease, particularly heart failure, is one of the most prominent health challenges of the modern era, ranking among the leading causes of death worldwide. The incidence of this disease is linked to several factors, including advanced age, gender, and genetic factors, along with unhealthy lifestyles such as low levels of physical activity, poor diet, smoking, and constant exposure to stress and psychological pressure. With the rapid changes in lifestyles and the rising incidence rates, prevention and early diagnosis have become of paramount importance in managing this disease.

The effects of heart disease extend beyond physical health to include reduced quality of life for patients, in addition to the significant economic burden it places on healthcare systems around the world, given the need for regular medical follow-up, long-term care, and sometimes expensive therapeutic interventions such as surgery or catheterization. Therefore, implementing early screening strategies is a crucial step in reducing the risk of disease progression and limiting its effects. Medical research indicates that early detection of risk factors, such as high blood pressure, high cholesterol, and blood sugar, can effectively reduce the risk of developing the disease and open the way for early intervention, whether through lifestyle modification or initiating drug treatment in its early stages.

In light of advances in data analysis technologies, the classification of health data related to heart disease has become a pivotal tool for supporting diagnostic and preventive efforts. With the availability of a vast amount of health information generated from medical records and clinical examinations, artificial intelligence and machine learning techniques can be employed to discover patterns and analyze the links between the various factors that contribute to the development of the disease. This type of classification helps develop accurate predictive models that help identify individuals most at risk, enabling healthcare providers to direct therapeutic interventions more efficiently.

This scientific methodology, based on knowledge and systematic analysis, is consistent with Islamic values, which emphasize reason, science, and reflection in making sound decisions. God Almighty says:

بِسْمِ اللَّهِ الرَّحْمَنِ الرَّحِيمِ

﴿وَإِنِّي كُلَّمَا دَعَوْتُهُمْ لِتَغْفِرَ لَهُمْ جَعَلُوا أَصَابِعَهُمْ فِي آذَانِهِمْ وَاسْتَغْشَوْا ثِيَابَهُمْ وَأَصَرُّوا وَاسْتَكْبَرُوا اسْتِكْبَارًا﴾

صَدَقَ اللَّهُ العَظِيمُ (سورة نوح: 7).

This noble verse refers to the reactions of the people of Prophet Noah (peace be upon him) during his invitation. In Ibn Kathir's tafsir, it is stated:

بِسْمِ اللَّهِ الرَّحْمَنِ الرَّحِيمِ

(وَإِنِّي كُلَّمَا دَعَوْتُهُمْ لِتَغْفِرَ لَهُمْ جَعَلُوا أَصَابِعَهُمْ فِي آذَانِهِمْ وَاسْتَغْشَوْا ثِيَابَهُمْ),

meaning that they deliberately blocked their ears so as not to hear what Noah was calling them to. Likewise, Allah Almighty mentioned about the disbelievers of Quraysh:

بِسْمِ اللَّهِ الرَّحْمَنِ الرَّحِيمِ

(وَقَالَ الَّذِينَ كَفَرُوا لَا تَسْمَعُوا لِهَذَا الْقُرْآنِ وَالْغَوْا فِيهِ لَعَلَّكُمْ تَغْلِبُونَ)

(سورة فصلت الآية 26)

As for the phrase (وَاسْتَغْشَوْا ثِيَابَهُمْ), Ibn Jurayj narrated from Ibn Abbas that it means they disguised themselves so as not to be recognized. Sa'id ibn Jubayr and Al-Suddi mentioned that they covered their heads so they would not hear what was said. The term (وَأَصَرُّوا) indicates their persistence in great polytheism and disbelief, and (وَاسْتَكْبَرُوا اسْتِكْبَارًا) means their arrogance and refusal to follow the truth and submit to it From an analytical perspective, and in comparison, with the concept of data classification, several points can be inferred:

Classification of reactions: The verse describes multiple patterns of reactions from the people of Noah toward the invitation, including deliberate neglect (placing fingers in ears), concealment and refusal to listen (covering with garments), persistence in rejection, and arrogance.

Classification of behaviors into categories: These patterns can be considered as "categories" or "classifications" of individuals’ behavior, where behavioral data are grouped into distinct sets based on observable traits.

Identification of distinctive features: The mentioned actions (covering ears, hiding face, persistence, arrogance) represent features that can be used as inputs in an analytical model for behavioral classification.

Analytical model: Similar to data science practices where individuals are classified into groups (e.g., responsive, rebellious, ignoring, arrogant) based on behavioral data, this verse reflects a primitive form of the same principle.

Impact of classification on outcomes: Based on this behavioral classification, their fate was (the flood), indicating that classification is not merely an organizational process but has clear consequences affecting the destiny of classified groups.

Therefore, this verse represents an innate and intuitive model for classifying human behavioral data based on descriptive observations, which aligns with the principles used by data scientists and specialists to analyze and predict individuals' behavior using precise and clear data and classifications.

The noble hadith implicitly indicates a form of data or information classification by distinguishing between people actions or intentions based on their characteristics which can be considered a type of featurebased classification as narrated in Sahih Muslim Hadith No 2638 repeated from Abu Huraira radi allah eanh who said rasul allah ﷺ said

الناس معادن كمعادن الفضة والذهب خيارهم في الجاهلية خيارهم في الإسلام إذا فقهوا والأرواح جنود مجندة فما تعارف منها ائتلف وما تناكر منها اختلف

In this noble hadith the rasul allah ﷺ illustrates the nature and diversity of people using an eloquent style that combines metaphor and classification in his saying (الناس معادن كمعادن الذهب والفضة) people are like mines of gold and silver he compares people to metals in terms of the variety of their temperaments and the differences in their value just as some metals are precious like gold and silver and others are of lesser value people too differ some are generous truthful and brave while others are not this comparison shows that human differences are innate and essential and that every individual has a unique nature just as metals vary in their inherent properties

The rasul allah ﷺ then presents an important criterion for evaluating individuals in his saying (خيارهم في الجاهلية خيارهم في الإسلام إذا فقهوا) the best among them in the preIslamic era are the best in Islam if they gain understanding this means that those who possessed noble traits such as generosity courage and honesty before Islam often retain those qualities after embracing Islam and they become even better when enriched with knowledge and understanding this highlights that Islam does not erase innate virtues but rather refines and elevates them

His saying (والأرواح جنود مجندة فما تعارف منها ائتلف وما تناكر منها اختلف) souls are like enlisted soldiers those that recognize one another will come together and those that reject one another will differ expresses a deep truth about the harmony or dissonance between souls sometimes a person may feel connected to someone they just met or feel distant from another without a clear reason the secret lies in the affinity or discord among souls which operates on a spiritual level beyond material or visible factors

In his Sharh Sahih Muslim Imam alNawawi volume sixteen Book of Birr and Silah Chapter Souls are like Enlisted Troops explained that the saying People are minerals

means their origins differ in good and evil just as metals differ among them are those with noble origins like gold and silver and others who are not goodness in the preIslamic era refers to generosity bravery and honesty if they embrace Islam and gain knowledge they become better

As for the indication of data classification the hadith implicitly classifies people based on innate characteristics through the metaphor of metals behavioral and cognitive transformation through knowledge and understanding and spiritual harmony through soul affinity or dissonance

Thus the hadith provides a refined prophetic foundation for understanding and classifying human diversity based on inner qualities rather than superficial appearances this aligns with modern concepts in data science particularly featurebased classification used in contemporary information systems

The comparison of people to metals and souls to grouped soldiers carries an implicit reference to categorizing individuals based on internal attributes and essential traits rather than their outward form it reflects a deep perception of human diversity and resonates with modern analytical methods that seek to classify data based on meaningful and impactful features

In 2020, the number of people suffering from heart failure worldwide was estimated at around 64 million. This number reflects an upward trend in the incidence of the disease associated with several factors, such as an aging population and the increasing prevalence of chronic diseases such as hypertension and diabetes, this year posed a major challenge to health systems around the world, as these challenges coincided with the health and economic impacts resulting from the COVID-19 pandemic, This continuous increase in the number of patients highlighted the urgent need to improve strategies for the prevention, diagnosis and effective treatment of heart failure.

In 2021, the number of people with heart failure increased to 64.5 million worldwide. This increase continues due to population aging and the increase in lifestyle risk factors such as obesity and smoking. Studies show that one in five people are at risk of developing heart failure during their lifetime, which calls for intensifying preventive healthcare efforts. In addition, recommendations have increased for the introduction of early diagnosis techniques and continuous follow-up to improve patients' quality of life and reduce complications of the disease.

By 2022, the number of people suffering from heart failure has increased to about 65 million people worldwide this increase in the number of cases has led to an increase in the burden on systems these numbers represent a significant financial and health burden, prompting medical communities to focus on improving the effectiveness of therapeutic and preventive interventions, in addition to exploring new technologies to alleviate this growing burden.

In 2023, the number of people with heart failure increased to 65.5 million people worldwide this increase is attributed to the continued prevalence of risk factors such as high rates of obesity and high blood pressure, In addition, this year witnessed significant progress in the use of modern technologies such as artificial intelligence to improve the process of early diagnosis and more effective management of the disease, These developments contribute to improving the quality of life for patients and reducing death rates associated with the disease.

In the year 2024 (estimated), the number of people with heart failure globally is expected to reach approximately 66 million people by 2024 these projections are based on the continuation of current trends in risk factors such as population aging and the increased prevalence of lifestyle-related diseases in contrast, improvements are expected to lead to in diagnosis and treatment, more cases will be discovered, which may increase pressure on health systems Therefore, innovations in health care, such as advanced prevention strategies and the introduction of sustainable care systems, are expected to become increasingly important.

The following table shows the number of people with heart failure from 2020 to 2024.

Table 1.1 Number of People with Heart Failure From (2020–2024).

Year	**Number of people with heart failure (million)**
2020	64 million
2021	64.5 million
2022	65 million

Year	Number of people with heart failure (million)
2023	65.5 million
2024	66 million

These figures are estimates and are based on global reports from the World Health Organization (WHO) and the American Heart Association (AHA)Statistics indicate that the number of people with heart failure will increase from 64 million in 2020 to about 66 million in 2024 this increase represents an additional 2 million people over a period of four years, reflecting an upward trend as shown in Figure(1.1), This growth in numbers reflects not only the health challenges facing individuals, but also the increasing pressures on global health systems.

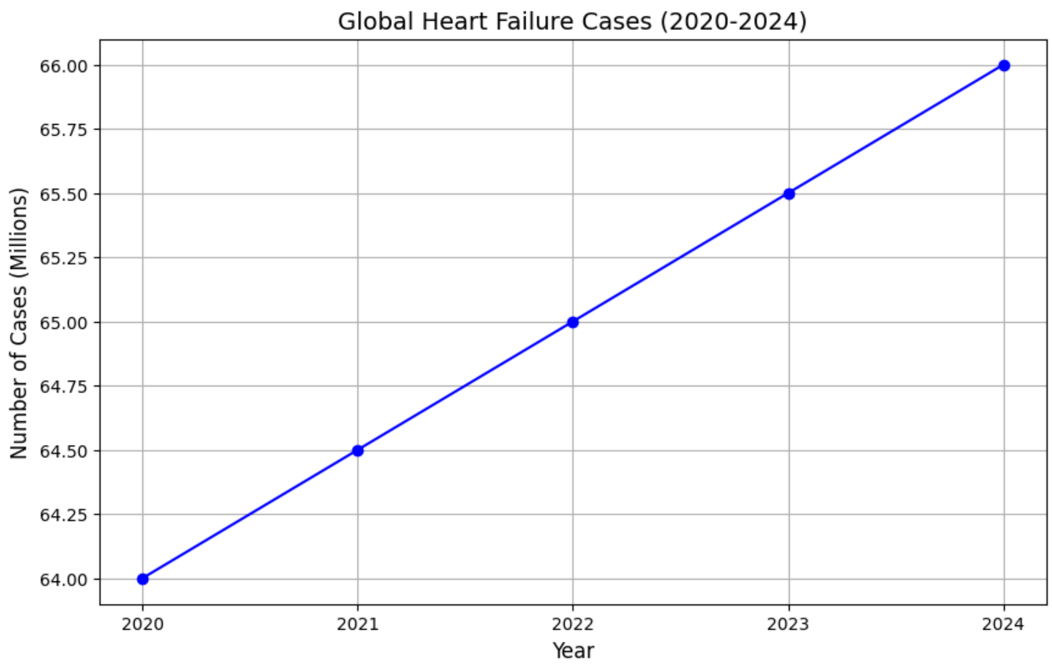

Figure (1.1) People with disease chart around the world

The number of people with heart failure is expected to increase by about 3.1% between 2020 and 2024, from 64 million to 66 million people, this reflects the ongoing upward trend in the incidence of heart failure, which calls for greater attention from public health decision-makers to develop effective strategies to address this growing problem.

There are several key factors contributing to the increase in heart failure cases, the most prominent of which is the increasing age of the population Aging is a major risk factor for heart disease, as many older adults suffer from other chronic diseases that affect heart health. In addition, the increase in risk factors, such as obesity, high blood pressure, and diabetes, contribute significantly to the prevalence of heart failure. Research indicates that these factors place individuals at high risk, which reinforces the need to adopt effective preventive strategies.

The source of information on previous statistics on heart failure is mainly based on global reports from leading health organizations such as the World Health Organization (WHO) and the American Heart Association (AHA), These organizations collect health data from all over the world and issue annual reports that include statistics on the prevalence of chronic diseases, including heart failure. These reports also provide information on risk factors, associated health costs, and incidence rates.

1.2. Questions of the Problems

1. How can heart failure be predicted?
2. What is the accuracy rate of heart failure prediction?

1.3. Objectives

1. Predict heart failure using data mining technology.
2. Obtain high prediction rate to predict heart failure.

1.4. Research Benefit

This research aims to predict heart failure using data mining technology, which relies on analyzing large amounts of health data to extract patterns and indicators that may indicate the possibility of heart failure. The research focuses on using multi-layer neural network (MLP) algorithms to analyze data related to the health status of patients. Through these advanced analytical models, doctors can predict the health status of the patient at an early stage, allowing them to take appropriate therapeutic measures in a timely manner. This research contributes to improving the accuracy of early diagnosis, enhancing the quality of health care, and reducing the risk of complications associated with heart failure.

1.5. Scope of Problems

Data quality This factor indicates that the data used in the study may be insufficient, which may negatively affect the accuracy and validity of the study results. Data analysis This factor indicates that the data analysis process may be complex and requires expertise in data mining and statistical techniques to ensure the accuracy of conclusions, and the selection of important variables. This factor indicates the difficulty of correctly identifying the main factors affecting the predictions, which may affect the accuracy of prediction models and the interpretation of results. This factor indicates the challenges that the researcher may face in interpreting the results and understanding the relationships between variables, especially if there are multiple effects and controlling the variable factors. This factor indicates that there are other unstudied factors that may affect the results of the study, making it difficult to achieve high accuracy in predictions and rely on prediction models. This factor indicates that the results of prediction models may not be accurate enough to be relied upon to make critical medical decisions.

Chapter II

Study literature

2.1 Related work.

Divya Vani (2021) in her research paper aims to predict heart failure using an improved Long Short-Term Memory (LSTM) model The proposed model focuses on improving the prediction performance by handling irregular temporal data, where the use of an improved “Forget Gate” within the LSTM is proposed to achieve this, irregular time periods were smoothed to a reasonable range and then used as inputs to the gate, which helps overcome the obstacles related to irregular data. The experimental results of the improved model, called T-LSTM-TR, showed significant performance improvements compared to the traditional model, especially in indicators such as data recall (Recall) and overall accuracy (AUC), where the AUC in the improved model reached 0.896 compared to 0.844 in the traditional model, proving the effectiveness of the proposed improvements in predicting heart diseases. One of the most notable aspects of this study is testing the effect of longitudinal data on prediction accuracy the experiments showed that when longitudinal data is presented separately (at intermittent time periods) to the LSTM model, the accuracy of the model increases compared to presenting the data in aggregate the experiments also showed that the model maintains a high level of accuracy even with a reduction in data size, which enhances its effectiveness and flexibility when dealing with smaller data sets.

Jane Preetha Princi et al. (2020) presented a study aimed at predicting heart disease using several supervised machine learning algorithms, such as decision tree, logistic regression, random forest, support vector machine (SVM), k-nearest neighbor (KNN), and Naive Bayes these models were tested on a dataset related to heart disease that included 12 features and aimed to determine whether a person had heart disease, The results showed that decision tree performed best with a predictive ability of 73%, followed by logistic regression and support vector machine with an accuracy of 72%, and random forest with an accuracy of 71%. Other models, such as KNN and Naive Bayes, performed less well with an accuracy of 66% and 60%, respectively the researchers explain that decision tree provides an effective means to support doctors in diagnosing heart disease early and providing appropriate treatment the study emphasizes the importance of using such models in predicting chronic diseases, as they can help in early detection and provide intervention strategies to delay or prevent the development of the disease.

Rüstem Yılmaz et al (2021) aim in their paper to develop a predictive classification model for identifying risk factors for heart attacks using advanced neural network techniques. The study relied on the analysis of a comprehensive dataset containing medical records of 303 patients, of which 54.5% were at high risk for heart attacks. The researchers employed two models: the multilayer perceptron (MLP) and the radial basis function (RBF) neural networks. The MLP model achieved the best results with an accuracy of 91.1%, F1 score of 91.8%, specificity of 92%, and sensitivity of 90.3%, while the RBF model attained an accuracy of 79.7% and F1 score of 81.2%. The most critical variables identified were resting blood pressure (trestbps), ST depression induced by exercise (oldpeak), and cholesterol (chol). The researchers concluded that the MLP model provides highly accurate predictions, which can assist healthcare professionals in diagnosing heart attacks early, thereby improving patient outcomes and aiding in timely medical interventions.

Laila Rasmy et al. (2018) presented a study that aimed to evaluate the ability of the recursive neural network (RNN) model "RETAIN" to predict the risk of heart failure onset using large and diverse electronic health records (EHR) data the model used the RNN algorithm with reverse attention mechanism to deal with the time series of medical data from more than 600 hospitals the data included about 150,000 heart failure patients and more than 1 million from the control group the results showed that the RETAIN model achieved an accuracy of 82% (AUC), outperforming the logistic regression model that recorded 79%, confirming the effectiveness of deep learning models in medical prediction Moreover, it was found that the prediction accuracy varies between different patient groups and hospitals, with the model being applicable across other hospitals with a slight decrease in performance, supporting the model's broad generalizability.

Edward Choi et al. (2017) analyzed the effectiveness of a recurrent neural network (RNN) model based on a recurrent gate unit (GRU) for early detection of heart failure, using temporal data extracted from electronic health records (EHR). The study aimed to explore whether models that take into account the temporal relationships between events can improve the accuracy of predicting the initial diagnosis of heart failure compared with traditional models. The performance of the GRU model was evaluated by comparing it with several other algorithms, such as logistic regression, multilayer neural network (MLP), support vector machine (SVM), and k-nearest neighbors (KNN) algorithm. The results indicated that the GRU model performed well, with an AUC of 0.777 using a 12-month observation window, which improved to 0.883 when the window was extended to 18 months. In comparison, the MLP model achieved an AUC of 0. 834.

Xing Han Lu et al. (2021) proposed an advanced recurrent neural network (RNN) model called the Deep Heart Failure Trajectory Tracking Model (DHTM), which aims to predict the progression of heart failure over time based on electronic health record (EHR) data of patients with congenital heart defects, The model was developed to predict the future occurrence of heart failure and also to identify associated comorbidities, The researchers added an improved model called DHTM+C to predict other comorbidities, The DHTM+C model achieved higher accuracy in predicting long-term heart failure compared with traditional models such as LSTM and statistical models such as Cox analysis, The AUC value of the DHTM+C model was about 0.8626, outperforming other models in predicting future time points of cardiac events in patients, demonstrating its effectiveness in enhancing the accuracy of long-term prediction and achieving flexibility in using the model to analyze the progression of chronic diseases.

Irfan Javid et al, (2020) presented a study that aimed to improve the accuracy of heart disease prediction using a combination of machine learning models and recursive neural networks (RNNs) through majority voting, The study used the University of California heart disease dataset, and the researchers tested machine learning techniques such as random forest, support vector machine (SVM), and k-nearest neighbors (KNN), along with deep learning models such as LSTM and recurrent memory units (GRU), The results showed that the combined model using majority voting achieved an accuracy of 85.71%, outperforming individual models such as random forest which achieved an accuracy of 83.6%, demonstrating the effectiveness of the voting model in enhancing the accuracy of heart disease prediction by aggregating the predictions of weak models to achieve better performance.

Sandas Naqib Khan et al, (2017) conducted a study aimed at comparing the performance of different algorithms for predicting heart diseases using data mining techniques, The researchers used tools such as RIPPER, decision tree (C4.5), artificial neural networks (ANN), and support vector machine (SVM) to develop prediction models. The algorithms were applied to a dataset containing 14 features and 296 records after handling missing values. The results showed that SVM achieved the highest accuracy of 84.12%, followed by RIPPER with an accuracy of 81.08%, and ANN with an accuracy of 80.06%, while the decision tree was the least accurate with an accuracy of 79.05%, The study concluded that SVM is the most effective in classifying heart diseases among the models used, which supports its use as an aid to doctors in early diagnosis.

Ali Al Bataineh (2022) aimed in their study to develop a hybrid predictive model, MLP-PSO, to enhance the diagnosis of heart disease. Using the Cleveland Heart Disease dataset, which includes 303 instances with 13 medical features, the researchers explored multiple machine learning models. The proposed MLP-PSO model, combining a multilayer perceptron (MLP) with particle swarm optimization (PSO), achieved the highest performance, with an accuracy of 84.61%. Comparatively, other models, such as decision trees and random forests, exhibited lower accuracy rates. This study highlighted the effectiveness of MLP-PSO in providing more precise predictions, aiding early diagnosis, and improving healthcare decision-making processes for heart disease detection.

Ramin Asari et al. (2017) presented a study aimed at improving the accuracy of heart disease diagnosis using data mining techniques the researchers relied on decision tree, Bayesian network, K-Nearest Neighbor, and Support Velocity Machine (SVM) algorithms, where they applied these algorithms to the Cleveland Clinic Foundation dataset for heart disease. The results showed that the SVM algorithm achieved the best performance among the other algorithms with an accuracy of 84.33%, followed by the Naïve Bayes algorithm with an accuracy of 83.66%, while the decision tree and the nearest neighbor function achieved lower accuracy, The study identified the most influential factors in the prediction, which are "thal", "ca", and "cp", as these variables were the most important in improving the accuracy of the predictive model, which confirms the effectiveness of these algorithms in the early diagnosis of heart diseases.

Daniel Anani-Obere et al. (2020) presented a study aiming to improve the prediction of heart disease using machine learning techniques, in order to reduce the number of diagnostic tests required, the researchers used three algorithms, namely Gaussian Naïve Bayes (GNB), Logistic Regression (LR), and Decision Tree, to analyze the Cleveland Heart Disease dataset containing 303 samples and 14 features. The models were evaluated using accuracy, 10-fold cross-validation, and ROC-AUC curve. The results showed that the GNB and LR algorithms achieved the best performance with an accuracy of 82.75%, with a slight superiority for GNB with an AUC value of 0.87 compared to 0.86 for logistic regression, highlighting the effectiveness of GNB in predicting heart disease with high accuracy.

In a study by Bo Jin et al. (2018), a long-short-term memory (LSTM)-based model was designed to predict heart failure risk using electronic health record (EHR) data the study focused on improving the prediction accuracy by using various data representations, such as one-hot encoding and word vectors, to represent diagnostic events the results showed that the LSTM model significantly outperformed traditional algorithms, including Logistic Regression (LR), Random Forest (RF), and AdaBoost the word vectors-based model achieved ROC-AUC = 0.81 and PR-AUC = 0.79, compared to ROC-AUC = 0.74 and PR-AUC = 0.71 using one-hot encoding these results support the effectiveness of the LSTM model in improving the accuracy of heart failure risk prediction by exploiting temporal relationships and representing data more efficiently.

Jacob Scott (2023) aimed in his paper to develop a deep learning model for predicting in-hospital mortality among ICU patients diagnosed with heart failure (HF), using data from the MIMIC-IV database. The study focused on integrating three datasets: static patient information, temporal event data, and bedside monitoring vitals aggregated into 5-minute intervals. The primary objective was to create an early warning system leveraging the first 48 hours of patient data post-ICU admission the research employed logistic regression as a baseline and a multilayer perceptron (MLP) neural network with focal loss to handle severe class imbalance. The fully integrated MLP model achieved the best results, with a minority-class F1-score of 0.58 and a ROC-AUC of 0.8786, after optimizing the classification threshold. The study demonstrated that integrating multiple data modalities and fine-tuning model thresholds could significantly improve mortality prediction, providing a valuable tool for early interventions in critical care settings.

Abdalla Mahgoub (2023), aimed in his paper to develop a novel approach for predicting and classifying heart failure using advanced machine learning and deep learning techniques. The study utilized a multi-dimensional dataset of 1,025 records with 14 selected features. Two methodologies were employed: traditional supervised machine learning algorithms (e.g., SVM, KNN, and Logistic Regression) and deep learning via Multilayer Perceptrons (MLPs), among the machine learning models, the SVM achieved the best accuracy of 89%, while the

MLP model demonstrated robust performance with an average accuracy of 84.26% using various activation functions (ReLU, Tanh, and Logistic). The MLP model particularly excelled in adapting to real-life scenarios with iterative self-learning. The study highlighted critical features like chest pain type, cholesterol levels, and ST depression induced by exercise,the author concluded that the MLP framework offers a scalable and efficient solution for heart failure prediction, with potential for further enhancements through larger datasets and optimized neural architectures. This approach aids in early detection, improving medical decision-making and patient outcomes.

Sahyajaet al. (2023) aimed in their paper to predict cardiac arrest using a Multilayer Perceptron (MLP) classifier implemented in Python. The study utilized a dataset collected from Kaggle and supplemented it with test data from hospitals in Vijayawada, India, involving a sample size of 120 respondents. The authors employed judgmental sampling techniques to analyze patient data and identify critical risk factors associated with heart failure, the MLP model was trained and evaluated using features such as age, creatinine levels, and serum sodium levels. Results indicated an accuracy of 75%, demonstrating the potential of MLP in predicting cardiac events effectively. The study emphasized the importance of lifestyle interventions for patients with high serum creatinine and blood pressure levels to mitigate risks. This research provides valuable insights for healthcare professionals, aiding in early detection and preventive care for cardiac patients.

Osei and Baafi-Adomako (2024) aimed in their paper to compare the performance of various machine learning algorithms for predicting heart failure. The study used the Heart Failure Prediction Dataset from Kaggle, which includes 918 observations with 12 features. The models evaluated included Random Forest (RF), Support Vector Machine (SVM), Gradient Boosting (GB), Logistic Regression (LR), Decision Tree (DT), Gaussian Naive Bayes (GNB), K-Nearest Neighbors (KNN), and an Artificial Neural Network (ANN), the Random Forest model achieved the highest accuracy of 90%, followed by SVM with 88% and ANN with 87%. RF also excelled in precision, recall, and F1-score, scoring 90% across these metrics, as well as an AUC of 95%. The analysis emphasized critical features, including chest pain type, fasting blood sugar levels, and ST slope, as key contributors to predicting heart failure, the authors concluded that RF is the most effective model for heart failure prediction, offering superior performance metrics and robust reliability. They recommended further research to include larger datasets and advanced techniques like deep learning and transfer learning to enhance model accuracy and generalizability.

2.1.1 Compare data analysis methods and algorithms.

Comparing data analysis methods and algorithms plays a pivotal role in enhancing understanding and improving the performance of predictive models, especially in the fields of healthcare and in the field of heart disease prediction. Multiple techniques are used to analyze data and extract the most accurate results the process of comparing these methods contributes to determining the most effective method according to the nature of the data used and the desired goals through these comparisons, diagnostic tools can be improved and accurate medical solutions can be provided that support better therapeutic decision-making he following table shows a comparison between studies.

Table (2.1) Comparison of Studies.

Author & Year	Algorithms Used	Result	Study Objective
Divya Vani (2021)	Improved LSTM (T-LSTM-TR)	AUC: 0.896	Enhancing heart failure prediction accuracy using an improved LSTM model.
Jane Preetha Princi et al. (2020)	Decision Tree, Logistic Regression, SVM, KNN, Naive Bayes	Best: Decision Tree 73%	Comparing machine learning algorithms for heart disease prediction.
Rüstem Yılmaz et al. (2021)	MLP, RBF Neural Networks	MLP: Accuracy 91.1%, F1 91.8%	Evaluating neural networks' performance in heart disease diagnosis
Laila Rasmy et al. (2018)	RNN (RETAIN)	AUC: 82%	Using deep learning to identify temporal patterns in electronic health records
Edward Choi et al. (2017)	RNN (GRU)	AUC: 0.883 (18-month window)	Improving heart failure prediction using temporal data
Xing Han Lu et al. (2021)	RNN (DHTM, DHTM+C)	AUC: 0.8626	Tracking long-term heart failure progression
Irfan Javid et al. (2020)	Random Forest, SVM, KNN, LSTM, GRU (Majority Voting)	Accuracy: 85.71%	Combining multiple models to improve heart disease prediction accuracy
Sandas Naqib Khan et al. (2017)	SVM, RIPPER, ANN, Decision Tree	Best: SVM 84.12%	Comparing traditional and modern algorithms for heart disease prediction
Ali Al Bataineh (2022)	MLP + (PSO)	Accuracy: 84.61%	Enhancing heart disease prediction models using AI

Author & Year	Algorithms Used	Result	Study Objective
Ramin Asari et al. (2017)	Decision Tree, Bayesian Network, KNN, SVM	Best: SVM 84.33%	Analyzing key factors influencing heart disease prediction
Daniel Anani-Obere et al. (2020)	GNB, Logistic Regression, Decision Tree	Best: GNB 82.75%	Comparing ML algorithms for heart disease prediction using the Cleveland dataset
Bo Jin et al. (2018)	LSTM	ROC-AUC: 0.81 (Word Vectors)	Improving predictive accuracy through word vector representations in electronic health records
Jacob Scott (2023)	MLP (with focal loss), Logistic Regression	ROC-AUC: 0.8786	Integrating static and temporal data for improved heart disease prediction
Abdalla Mahgoub (2023)	SVM, KNN, Logistic Regression, MLP	Best: SVM 89%	Identifying critical factors associated with heart disease using AI techniques
Sahyaja et al. (2023)	MLP	Accuracy: 75%	Investigating major risk factors for heart disease
Osei and Baafi-Adomako (2024)	RF, SVM, GB, LR, DT, GNB, KNN, ANN	Best: RF 90%	Analyzing key factors affecting heart disease prediction using ML

By analyzing the studies in the table, Rüstem Yılmaz et al. (2021) achieved the highest performance, with an accuracy of 91.1% and an F1-score of 91.8% using the Multilayer Perceptron (MLP). The study evaluated the effectiveness of MLP and RBF Neural Networks in diagnosing heart disease, demonstrating MLP’s superior performance in identifying critical predictive factors.

Similarly, Ali Al Bataineh (2022) enhanced MLP using Particle Swarm Optimization (PSO), achieving an accuracy of 84.61% on the Cleveland Heart

Disease dataset. This integration optimized the neural network's weight selection, improving its classification performance.

Other studies have also utilized MLP for heart disease prediction. Sahyaja et al. (2023) investigated key risk factors using MLP, achieving 75% accuracy, while Jacob Scott (2023) combined MLP with focal loss and logistic regression, obtaining an AUC of 0.8786 by integrating static and temporal data.

Furthermore, Irfan Javid et al. (2020) incorporated MLP within an ensemble framework alongside Random Forest, SVM, KNN, LSTM, and GRU, resulting in an accuracy of 85.71%, reinforcing the effectiveness of MLP-based models in heart disease prediction.

In summary, MLP and its optimized variations, such as MLP + PSO, consistently deliver high performance in heart disease classification, making them among the most effective deep learning techniques for predicting heart failure progression

A variety of variables have been used in previous studies, with each study varying based on the scope of the research and the analysis methods used. This table provides a comprehensive analysis of the different uses of variables in multiple studies related to heart health research. Algorithms were selected based on their efficiency in processing and analyzing medical data. The table includes information about the names of the authors and the dates of the studies, in addition to the variables used in each study.

The characteristics and abbreviations used in the studies include variables as follows: A refers to age, S refers to gender, CPT refers to chest pain type, RBP refers to resting blood pressure, C refers to cholesterol, FBS refers to blood sugar level, REC refers to resting electrocardiogram, MHR refers to maximum heart rate, EA refers to angina pectoris on exertion, O refers to elevation, SS refers to ST slope, and finally HD refers to heart disease. These are the most prominent characteristics used.

Table (2.2) Variables used in literature reviews.

Author and Year	**A**	**S**	**CPT**	**RBP**	**C**	**FBS**	**REC**	**MHR**	**EA**	**O**	**SS**	**HD**
Divya Vani (2021)	1	1	0	1	1	1	0	1	1	0	1	1
Jane Preetha Princi et al. (2020)	1	0	1	0	1	0	1	1	1	1	0	1
Rüstem Yılmaz (2021)	1	1	1	1	1	0	1	1	1	0	0	1
Laila Rasmy et al. (2018)	0	1	0	1	1	1	1	0	1	1	1	0
Edward Choi et al. (2017)	1	1	1	0	1	1	0	1	0	1	1	1
Xing Han Lu et al. (2021) ,	1	0	0	1	1	1	1	1	1	0	1	0
Irfan Javid et al, (2020)	1	1	1	1	0	1	1	0	1	1	0	1
Sandas Naqib Khan et al, (2017)	0	1	0	0	1	1	1	1	0	1	1	1
Ali Al Bataineh (2022)	1	1	1	1	1	1	0	1	1	0	1	0
Ramin Asari et al. (2017)	0	0	1	1	1	1	1	1	0	1	0	1
Daniel Anani-Obere et al. (2020)	1	1	1	0	0	1	1	1	0	1	1	0

Author and Year	A	S	CPT	RBP	C	FBS	REC	MHR	EA	O	SS	HD
Bo Jin et al (2018)	1	1	0	1	1	0	0	1	1	1	0	1
Jacob Scott (2023)	1	0	1	1	1	1	1	1	0	1	1	1
Abdalla Mahgoub(2023)	1	1	1	0	1	1	0	1	1	1	1	0
Sahyaja (2023)	1	1	0	1	1	1	1	1	1	0	1	1
Osei and Baafi-Adomako (2024)	0	1	1	1	0	1	1	0	1	1	1	1

Previous studies show a diversity of variables used to assess heart disease, with age and gender used in all studies and resting blood pressure and cholesterol also being key variables, as they were used in most studies, highlighting their importance in diagnosing heart conditions.

Although chest pain type and resting ECG are widely used, there are some studies that do not include them. Variables such as maximum heart rate and angina on exertion are common, but not always present.

Variables associated with ST-segment slope and heart disease were found to be recurrent in most studies, indicating the importance of these factors in understanding cardiac risk. Overall, the results reflect the importance of using a variety of variables to achieve a comprehensive and accurate assessment of heart disease risk.

2.2 Theoretical framework.

This chapter deals with explaining the theoretical framework of the results of the literature study by classifying the parameters or variables as inputs to the theoretical framework data, and explains the methods used and the results extracted from the theoretical framework the theoretical framework can be seen in Figure (2.3).

Based on the theoretical framework derived from the results of the literature review, it can be concluded that heart disease prediction can be achieved with high accuracy using MLP the effectiveness and accuracy of these predictions depend largely on the quality of the input data and data verification the process of heart disease prediction begins with verifying the quality and reliability of the input data, where the consistency and correctness of the data are verified to ensure that it is free of errors and inconsistencies that may affect the accuracy of the models used later. This verification stage is considered the basis for ensuring the reliability of the predictions and comes as the first step to ensure that the data is valid for processing and analysis

After data validation, the next step involves cleaning and preparing the data to ensure its quality before analysis and prediction. This stage includes handling outliers, addressing missing values, and ensuring data consistency, all of which significantly enhance the accuracy of the models used for heart disease prediction. Improving data quality at this stage directly impacts the performance of predictive models by reducing errors and increasing the reliability of predictions.

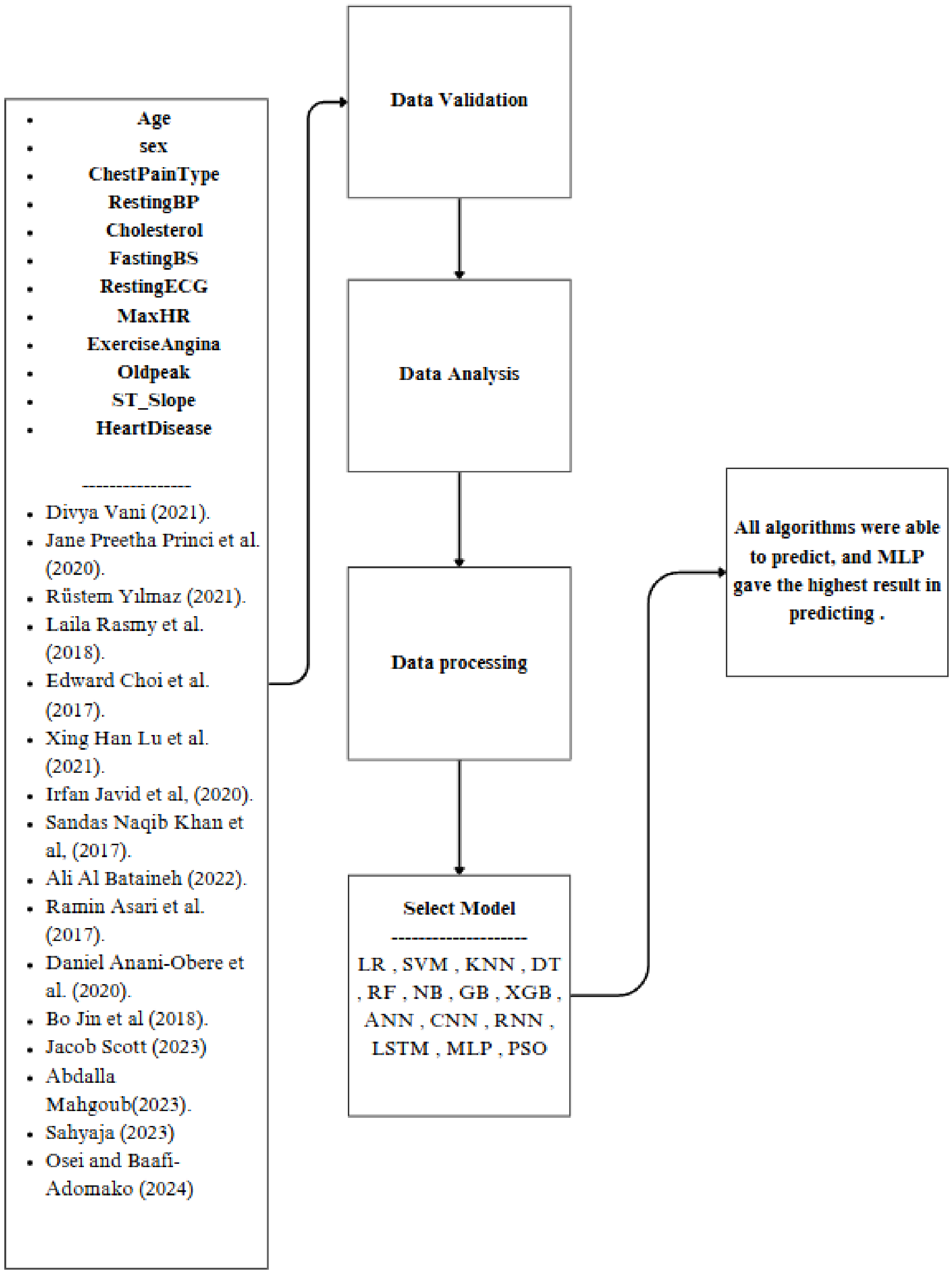

Figure (2.3) Theoretical Framework

In the data analysis phase, relationships between different variables are explored to identify key factors influencing the likelihood of developing heart disease. This analysis helps build more accurate models by providing a deeper understanding of the health factors affecting patients. Identifying patterns and correlations among variables contributes to improving the performance of predictive algorithms and helps determine the most important criteria for early disease diagnosis.

When selecting a predictive model, various statistical models and deep learning techniques are evaluated to determine which yields the best results. The models considered include deep and convolutional neural networks, as well as other techniques such as random forests, support vector machines, and ensemble learning methods like XGBoost. However, studies have shown that the multilayer perceptron (MLP) neural network is among the most efficient models for predicting heart disease, especially when dealing with non-temporal data or small and diverse datasets.

Several studies have demonstrated the strong performance of the MLP model in heart disease prediction. In a study by Rüstem Yılmaz et al. (2021), the model achieved an accuracy of 91.1%, an F1-score of 91.8%, a sensitivity of 90.3%, and a specificity of 92%. These results confirm the reliability of MLP as a valuable tool for supporting early diagnosis and improving healthcare outcomes. Additionally, studies conducted by Jacob Scott (2023) and Sahyaja et al. (2023) highlighted MLP's flexibility in handling various datasets, further enhancing its predictive accuracy and making it an effective model for clinical applications.

Although long short-term memory (LSTM) networks excel in handling sequential data, MLP remains a powerful model for static and diverse datasets.

However, its performance can be further enhanced by integrating it with particle swarm optimization (PSO), which efficiently fine-tunes the model's hyperparameters. PSO is inspired by the collective behavior of intelligent swarms in nature and is used to optimize key parameters of the model, leading to improved performance and reduced prediction errors.

Several studies have confirmed that combining MLP with PSO enhances heart disease prediction accuracy. A study by Bo Jin et al. (2018) demonstrated that the hybrid model significantly improved accuracy compared to traditional hyperparameter tuning methods. Similarly, research by Daniel Anami-Obere et al. (2020) found that integrating PSO with MLP helps refine learning parameters, layer configurations, and weight adjustments, leading to improved model stability and overall performance. Furthermore, a study by Osei and Baafi-Adomako (2024) confirmed that using PSO with MLP achieves superior results compared to conventional algorithms, offering higher accuracy and improved computational efficiency.

The MLP model is one of the most robust predictive models for diagnosing heart disease, particularly when dealing with static or multidimensional datasets. Moreover, integrating PSO with MLP enhances its performance, making it more accurate and efficient. This combination presents an ideal approach for supporting medical diagnosis and predicting health risks associated with heart disease. Therefore, focusing on MLP, supported by PSO, can provide more reliable solutions for medical data analysis and heart disease prediction.

Chapter III

Research Methodology

3.1 Research Design.

This research aims to study heart failure and improve the accuracy of its prediction, a disorder that affects the heart's ability to pump blood efficiently to meet the body's needs. Designing this research requires a scientific methodology that begins by defining the problem, reviewing the literature and previous studies, and then accurately collecting and analyzing data. The prediction results contribute to understanding the nature of the disease and its influencing factors, in addition to assessing its effects on patient health, with the goal of enhancing scientific understanding of this disease and its future impact.

1. Problems within the scope of the study: The study begins by identifying the main problem, namely the prevalence of heart failure and its increasing negative impact on the quality of life of patients and healthcare systems. A research question is formulated, with the aim of determining the significance of the study and the urgency of the problem for the healthcare community.
2. Literature review: This phase includes a review of previous studies and research on heart failure, including the techniques used, strategies, and accuracy of the findings. This literature is evaluated to determine what has been achieved and whether there are any knowledge gaps that need to be addressed. This review helps establish a theoretical foundation that guides the research and defines the conceptual framework used.

3. Data Collection and Tabulation: Data is collected from multiple sources such as hospitals, clinics, or through questionnaires and interviews with patients and doctors, Data can include information about disease conditions, treatments used, and treatment responses, this data is organized into tables to facilitate its subsequent analysis and extract important patterns and trends.
4. Qualitative Descriptive Analysis: In this phase, data are analyzed descriptively to explore the characteristics and patterns of heart failure, focusing on the physical and psychological factors affecting patients. The goal is to identify important variables and trends that influence disease progression, which will contribute to the development and training of machine learning algorithms to achieve more accurate predictions.
5. Interpreting analysis results: After completing the data analysis, the results are interpreted to understand the nature of the relationship between the factors contributing to heart failure and their impact on disease progression. This phase focuses on answering the research questions by demonstrating how the results contribute to advancing scientific understanding of the disease and supporting the development of more accurate predictive models using machine learning algorithms.
6. Discussion and Conclusion: In this phase, the results are discussed and linked to previous studies to demonstrate their consistency or discrepancy with the available scientific literature. The discussion highlights the new contributions that research offers in the field of heart failure prediction using machine learning

algorithms, summarizing the main findings and reviewing their importance in improving the accuracy of predictive models.

7. Limitations and Future Work: In this phase, challenges or barriers to research are highlighted, such as lack of data or limited sample size. Areas for future research are also suggested, such as new technologies to improve the lives of heart failure patients.

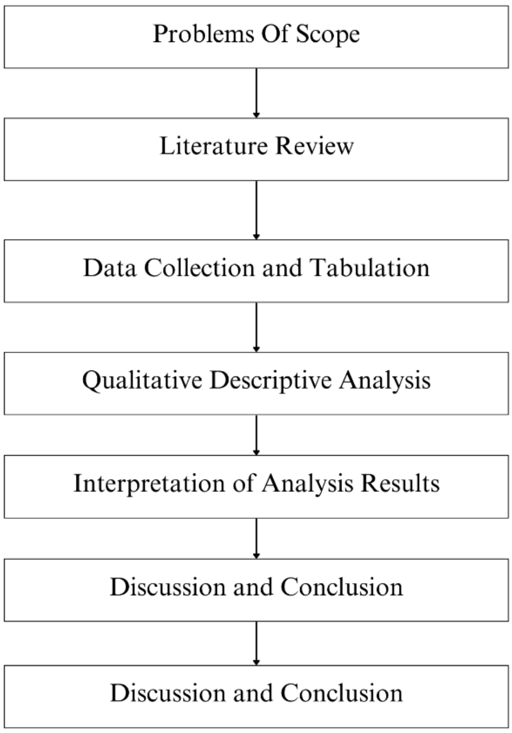

Figure (3.1) Flowchart for Research Methodology.

Research design refers to the plan that guides the study to understand heart failure and answer the research questions. Since this research focuses on developing a prediction model using the MLP algorithm and improving its performance, the design followed is an applied design based on a quantitative approach. This is accomplished by collecting relevant medical data, then training and testing machine learning models to analyze the relationship between the input factors and the occurrence of heart failure. This design aims to build a highly efficient predictive model that can detect significant patterns and more accurately predict heart failure cases, without involving the testing of clinical treatments or interventions.

3.1.1 Data collection.

Data collection is an essential step in research, as it provides the information needed to answer the study questions and verify its hypotheses, The accuracy of the results depends on the quality of the data collected. In the study of heart failure, this stage aims to understand the factors affecting the disease, evaluate the effectiveness of treatments, and analyze its impact on patients' lives. To ensure the reliability of the results, reliable data sources must be selected and accuracy and objectivity must be adhered to in collecting information. The research relies on the analysis of health and clinical indicators extracted from actual disease cases, which provides an in-depth understanding of the development of the disease and the impact of various therapeutic interventions.

3.1.1.1 Data Source.

Heart failure disease prediction data is an essential tool in medical studies, as it is collected from reliable sources that provide detailed information about health characteristics associated with heart disease. This data provides a variety of variables such as age, blood pressure, and cholesterol levels, enabling researchers to train accurate models to predict health risks. The Heart Disease Prediction dataset was obtained from Kaggle and collected from a university hospital in Prague, Czech Republic. It includes clinical information for 299 patients with 918 records suffering from heart disease, which is among the leading causes of death worldwide. The dataset consists of 12 key attributes, such as age, anemia, serum creatinine levels, cardiac output, and smoking status, to predict heart disease or mortality. This dataset is a valuable resource for machine learning research, enabling the development of models that help clinicians predict patient health outcomes based on their clinical characteristics.

3.1.1.2 Data attributes.

Input attributes are a key factor in developing heart failure prediction models, as the accuracy of the models depends on the quality and relevance of the data used. These attributes include various characteristics such as age, gender, type of chest pain, blood pressure, and cholesterol level, which are variables that studies have shown to be closely related to the likelihood of developing heart disease. These attributes play an important role in training models and guiding predictions, as they help uncover patterns and relationships that may not be immediately apparent by improving the selection of attributes and carefully processing the data, the effectiveness and accuracy of predictive models can be greatly enhanced the data attributes are as follows.

Table (3.1) Dataset attributes.

Name	Type
Age	int64
Sex	String
ChestPainType	String

Name	Type
RestingBP	int64
Cholesterol	int64
FastingBS	int64
RestingECG	String
MaxHR	int64
ExerciseAngina	String
Oldpeak	float64
ST_Slope	String
HeartDisease	int64

The heart failure prediction dataset comprises 12 attributes and 918 records, providing essential clinical data for predicting heart failure and associated mortality. These attributes include age, representing the patient's age in years, and fasting blood sugar (FastingBS), which indicates elevated blood sugar levels. Additionally, the dataset includes serum creatinine levels, reflecting kidney function, and resting blood pressure (RestingBP) as a measure of cardiovascular health. Other key variables include cholesterol levels (Cholesterol), resting ECG (RestingECG) findings, maximum heart rate (MaxHR), and ST slope (ST_Slope), all of which contribute to assessing cardiac risk. Furthermore, chest pain type (ChestPainType) and exercise-induced angina (ExerciseAngina) serve as indicators of heart stress. The dataset aims to predict heart disease (HeartDisease) based on these attributes, enabling the development of machine learning models to enhance early diagnosis and risk assessment.

3.1.1.3 Detailed features.

The input features play a crucial role in the accuracy of heart disease prediction models, as the model relies on a set of important variables that studies have shown to be closely related to the likelihood of infection. Among these features, we find age, which is associated with an increased risk of infection with age, and gender, which shows different effects on the likelihood of infection between men and women, the type of chest pain is also an important indicator that may be associated with the presence of blockage in the arteries, while blood pressure and cholesterol levels indicate the health of blood vessels. In addition to this, features such as fasting blood sugar, symptoms associated with physical activity such as shortness of breath, and features used in heart failure prediction models:

1. Age: Represents the patient's age in years and is one of the basic factors in assessing health risks. The likelihood of developing heart disease generally increases with age due to physiological changes and the accumulation of factors affecting cardiovascular health.
2. Gender (Sex): Refers to the patient's gender (male or female), as biological and hormonal differences play a role in determining the risk of heart disease between the sexes. For example, rates of infection in men are higher at an early age, while they increase in women after menopause.
3. Type of chest pain: Represents the type of chest pain felt by the patient, and includes several types, such as:

a. Non-specific pain: may not be associated with a specific activity.

b. Pain associated with effort: usually appears with effort and disappears with rest.

c. Stable pain: appears and disappears in a predictable pattern.

These differences help in assessing the severity of the condition and the possibility of a heart problem associated with the pain.

4. Blood pressure at rest: Resting blood pressure is measured in mmHg and high blood pressure is a major risk factor for heart disease, increasing the pressure on the arteries and increasing the risk of heart problems.

5. Cholesterol level: These variable measures the level of total cholesterol in the blood in milligrams per deciliter. High cholesterol, especially bad cholesterol (LDL), is associated with the accumulation of plaque in the arteries, which increases the risk of coronary heart disease.

6. Fasting blood sugar level: It expresses the blood sugar level after a period of fasting, and is an important indicator for assessing the likelihood of developing diabetes. Diabetes is a prominent risk factor for heart disease due to its association with vascular complications.

7. Resting electrocardiogram: This is the result of a resting electrocardiogram and can reveal problems with the heart's electricity, such as irregular heartbeats or evidence of an enlarged heart muscle, which may indicate the possibility of the patient developing heart disease.

8. Maximum heart rate :These variable measures the maximum heart rate that the patient can withstand while performing physical effort. Maximum heart rate is

an important measure of how well the heart can handle exercise or physical stress

9. Angina during exercise: Indicates whether the patient experiences chest pain during exercise or exertion. This symptom may indicate insufficient blood flow to the heart during exertion, indicating possible problems with the coronary arteries.
10. ST depression: Indicates a depression of the ST wave during a stress test, and is used to assess the heart's performance under stress. This depression is an indicator of insufficient myocardial ischemia, indicating possible blockage in the arteries.
11. ST slope :Measures the slope of the ST wave during a stress test. The slope of the ST wave is an indicator of the heart's response during exercise. Changes in slope may indicate insufficient myocardial ischemia, which is common in coronary heart disease.
12. Heart disease status: This variable represents whether the patient has heart disease or not (0 = not affected, 1 = affected). This variable is the primary target in prediction models, where models are trained on a set of previous features to determine the likelihood of heart failure.

Careful analysis and processing of these features is a vital step to increasing the accuracy of predictive models, as these features allow models to extract patterns and identify factors influencing the likelihood of infection, which contributes to enhancing the effectiveness and accuracy of predictions.

3.2 System Design.

This system relies on analyzing data from heart failure patients using a multilayer neural network (MLP) algorithm. The model is trained on a medical dataset to detect patterns and factors associated with disease occurrence. The model is tested on new data to measure its accuracy and effectiveness in predicting cases. Model optimization techniques are also used to increase prediction efficiency and reduce error rates. Continuous evaluation of the model's performance is conducted to ensure the development of an effective predictive system that supports accurate medical decision-making and contributes to improving the quality of healthcare.

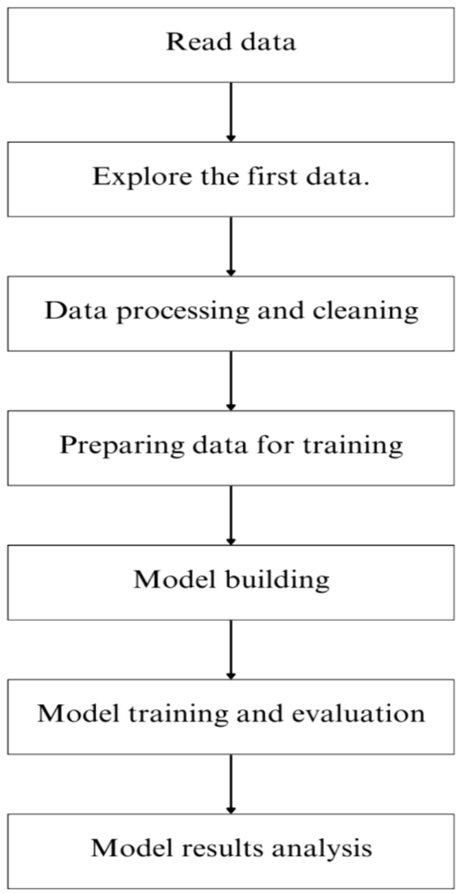

Figure (3.2) System Design.

The system that predicts heart failure relies on a series of steps that begin with collecting and analyzing data, then building the model, training it, and testing it on new data. Here are the details of each stage:

1. Read data: Data reading is a fundamental step, through which data is brought from various sources into the analysis environment. These sources include CSV text files. This step is pivotal because it ensures that the data is transferred accurately and properly to begin processing and analysis processes. The data import process greatly affects the quality of subsequent analysis. Errors in data reading may lead to inaccurate results. Although there are various ways to do this, this process may face challenges such as dealing with large data volumes that may affect the speed of import, and different data formats between sources, which requires additional effort to adjust them and ensure their consistency.
2. Explore the first data: After loading the data, an initial exploration process is carried out to understand the nature of the content and determine the characteristics of the data. A portion of the data is displayed to analyze its structure and to know the types of values available, such as numeric or textual values, and to know the existing characteristics such as age, gender, and cholesterol level. It is also ensured that there are a sufficient number of samples for each characteristic to evaluate its suitability for building the model. This step also shows if there is a large variation between the values or if there are missing values that may affect the accuracy of the results.

3. Data processing and cleaning: At this stage, the system performs a comprehensive data cleaning process by identifying and correcting incorrect or missing values, where some samples can be removed or missing values can be estimated based on the average values or replaced by other appropriate methods.

   If the data includes non-numeric features (such as texts or descriptive categories), it is converted into numeric representations that help the system understand and comprehend it correctly during the training process, If there is a large variance in the target categories (such as the number of patients with heart failure compared to the number of patients without), techniques are applied to balance the distribution of categories, This balance is necessary so that the model is not affected by the concentration of the most representative categories, which improves the model's ability to generalize to all categories.
4. After the data has been processed and cleaned, it is split into training and test sets at different ratios to evaluate the model's performance under various conditions. In each experiment, a certain percentage of the data is allocated to testing (ranging from 10%, 15%, 20%, up to 45%), while the remaining percentage is used to train the model using the MLP algorithm. This approach aims to measure the model's stability and accuracy as the size of the test data changes..
5. Model building: At this stage, the structure of the model is designed to be able to process the data and identify complex patterns in it. The model consists of a set of successive layers, where each layer learns certain patterns and passes its

results to the following layers. This arrangement enables the model to discover hidden patterns that are difficult for traditional techniques to understand. Elements may be added to the model to control the quality of generalization so that the model cannot save very specific details from the training set, which may lead to poor performance when dealing with new data, these elements allow the model to focus on general patterns that link different features and reduce its sensitivity to details that may be unimportant.

6. Model training and evaluation: After building the basic structure of the model, it is trained using the training data, The model is fed the data and adjusts its internal parameters so that it can recognize patterns that link the inputs and the target outputs. During this process, the system learns how to use different features to accurately predict outcomes.

   After training is complete, the model is tested on a test dataset that was not used in the training process. This aims to measure the accuracy of the model on previously unseen data and evaluate its ability to accurately predict heart failure cases.

   Evaluation metrics such as the percentage of correct predictions compared to incorrect ones are calculated, in addition to other performance indicators that help clarify how well the model distinguishes between positive and negative cases.

7. Analyzing the model results: After testing the model, additional analyses are conducted to examine the quality of its performance at various levels, including

measuring its accuracy in prediction and testing its ability to distinguish between classes correctly, Graphical displays are used to monitor and illustrate the effectiveness of the model, which helps identify points that can be improved.

If the model does not achieve the required level of accuracy, additional modifications are made to its structure or to the method of processing the data, and the model is retrained and tested until satisfactory performance is achieved. Possible improvements include modifying the number of layers, changing the distribution within the data, or increasing the size of the data used in training.

This system is a model for developing an accurate system for predicting heart failure using patient data based on an organized structure that begins with collecting and cleaning data, preparing it for training, and then building a model based on multiple layers that contribute to learning complex relationships between features.

3.3 System implementation.

Model implementation is a pivotal stage in transforming a theoretical concept into a practical application using the MLP algorithm. This stage begins by defining the technical requirements associated with the model, such as selecting appropriate features, defining the neural network architecture, and the criteria used for training. The model is then implemented using appropriate tools and techniques to improve efficiency and accuracy. This stage includes training the model on training data and then testing it using different proportions of test data to accurately assess its performance. The model results are also analyzed to verify the extent to which it achieves the research objectives of improving the prediction of heart failure.

3.3.1 Data processing and improvement.

Data processing is an essential step to ensure the quality and accuracy of predictive models for heart disease, table (3.3) shows the characteristics of the data type This process includes several stages to improve the quality of the data before using it in model training:

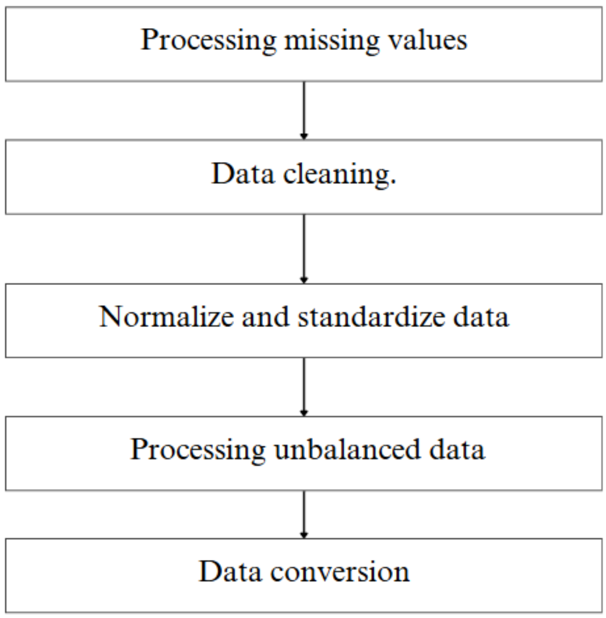

Figure (3.3) Data processing and improvement.

1. Treating missing values: Missing values in the data can negatively affect the accuracy of the model These values can be replaced by different methods such as using the mean, median, or predicting missing values.

2. Data cleaning: Involves removing abnormal and illogical values that may cause deviation in the results, as some of the entered values may be illogical or significantly different from the rest of the values, which requires their removal or modification.
3. Normalize and standardize data: This step is used to standardize the range of different values, especially when the data includes attributes with different measurements (such as blood pressure, cholesterol levels) Normalization helps to put all values within a specific range to facilitate learning and improve model performance.
4. Processing unbalanced data When the data is imbalanced (such as having more uninfected people than infected people), it can affect the accuracy of the prediction. Techniques such as under sampling or under sampling are used to achieve balance that helps the model learn better.
5. Data transformation: Involves the use of mathematical transformations to make features follow certain distributions, making it easier to understand patterns and relationships in the data This method is especially used for features that may be abnormally distributed Data optimization and processing is a vital step in developing disease prediction models. This process involves cleaning the data of errors and outliers, which helps reduce noise that may negatively affect the model's results. Data optimization also includes standardizing its format, so that all values are within a uniform range, which facilitates the analysis process and increases the efficiency of the model.

Furthermore, transformation techniques can be used to remove unnecessary information, allowing the model to focus on the most important features that influence the results This helps to enhance the accuracy of the model and its ability to generalize to new data. Techniques such as data partitioning play a key role in enhancing the performance of the model. By using independent data to test the model, its performance can be accurately evaluated and the problem of overfitting can be avoided.

3.3.2 Heart Failure disease Prediction System design.

It is a comprehensive design of heart failure prediction system, which aims to apply data mining techniques to analyze data and extract useful patterns, the system includes key components including data ingestion, model training, prediction and performance evaluation, machine learning algorithms and data mining techniques are used to improve the prediction accuracy and customize it according to users' needs, The following is the design of heart failure prediction system for this study.

1. Data Collection Layer: This is the first stage in data analysis, where data is collected from multiple sources to be ready for analysis. This layer aims to obtain accurate and comprehensive data that supports the construction of reliable predictive models, this process includes steps to examine and purify data to ensure its quality and format it in a way that is easy to use. Data quality in this layer is an important basis for achieving accurate and effective results in analysis and prediction, The data collection layer includes the following steps:

a. Check the data for quality:

i. Check for missing or invalid values.

ii. Check and distribute the values to ensure there are no deviations or abnormal data.

b. Data Cleaning:

i. Handle missing values using methods such as interpolation or elimination if necessary.

ii. Ensure that all values are consistent, such as converting text values to numeric values if necessary for analysis.

c. Identify key variables: Determine the variables that will be used in the heart failure prediction model, such as Age, Sex, RestingBP, Cholesterol, MaxHR, and HeartDisease.

d. Data Transformation:

i. Convert categorical variables such as Sex, ChestPainType, and RestingECG to numeric formats using numeric or categorical encoding (One-hot encoding).

ii. Perform the necessary transformations on variables that require normalization or standardization.

e. Save data in a form ready for analysis.

After the data has been prepared and cleaned, it can be saved to a new file or database so that it is ready for analysis and predictive models.

2. Data Organization Layer: After collecting the data, comes the step of organizing it to ensure that it is used effectively in building the model and generating recommendations. This layer includes:

a. Data Cleaning.

i. Removing missing or incorrect data.

ii. Handling missing values and correcting errors in data.

b. Feature Extraction.

i. Identify the most important features or variables that affect heart failure.

ii. Create derived indicators such as the rate of change in blood pressure or blood sugar level over time.

c. Data Normalization.

i. Converting data into a standardized format to make it compatible with the requirements of predictive models.

ii. Standardizing units and measurements to ensure accuracy of analysis (e.g. converting values from percentage to correlated system).

d. Data Partitioning:

i. Dividing data into training and test sets to ensure accurate evaluation of models.

ii. Using techniques such as cross-validation to distribute data appropriately.

e. Data Integration:

i. Integrating data from multiple sources such as hospitals, clinics, and medical reports.

ii. Linking time and interaction data with the patient's personal data to form a comprehensive file.

iii. The data organization layer ensures that all collected data is ready for use and analysis, helping to improve model performance and reduce errors caused by inaccurate or incomplete data.

f. Data Mining: It is the process of analyzing huge amounts of data with the aim of extracting patterns and valuable information. This layer uses various techniques from statistics and machine learning, such as classification and clustering, to discover hidden knowledge that can help organizations make informed decisions and improve performance. Data mining is of particular importance in fields such as marketing, healthcare, and finance, where it helps in identifying trends and analyzing future events.

i. Pattern Discovery: Clustering is a common technique used in pattern recognition and knowledge discovery. It involves grouping points so that points within the same group (or cluster) are more similar to each other than to points in other groups.

ii. Model Training: Model training involves splitting the data into training and test sets, often using techniques such as cross-validation to ensure robustness. Models are trained on labeled datasets with the goal of predicting outcomes. Training involves:

- Splitting the dataset into training and test sets using different ratios to evaluate the model's performance under different conditions. The initial split was 90% training and 10% testing (10:90), followed by repeated experiments using the following ratios: 15% testing and 85% training (15:85), 20% testing and 80% training (20:80), 25% testing and 75% training (25:75), 30% testing and 70% training (30:70), 35% testing and 65% training (35:65), 40% testing and 60% training (40:60), and finally 45% testing and 55% training (45:55). This sequence aimed to analyze the effect of different test set sizes on the model's prediction accuracy using the MLP algorithm.

- Implementing the models and evaluating their performance using metrics such as precision and recall.

g. Evaluation and Analysis layer: The evaluation and analysis layer are an essential part of data processing and analysis systems This layer is concerned with examining and evaluating the results of models or extracted data to ensure their accuracy and efficiency This stage includes the use of performance metrics to determine the effectiveness of models, such as the accuracy of predictions or the reliability of decisions It also provides statistical analyses and in-depth insights that are used to improve models and guide future strategies based on accurate results.

i. Model Performance Metrics: These metrics help evaluate the quality of the model from multiple angles.

Accuracy:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

Where:

- TP (True Positives): Number of correct positive predictions.
- TN (True Negatives): Number of correct negative predictions.
- FP (False Positives): Number of false positive predictions.

- FN (False Negatives): Number of false negative predictions.

Score F1:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (2)$$

Precision:

$$Precision = \frac{TP}{TP + FP} \quad (3)$$

Recall:

$$Recall = \frac{TP}{TP + FN} \quad (4)$$

The F1 score combines positive precision and recall to provide a balanced measure, which is especially useful in cases of imbalanced data.

Error Rate:

$$Error\ Rate = 1 - Accuracy \quad (5)$$

3.3.3 Model development.

Multilayer Perceptron (MLP) is one of the fundamental architectures in artificial neural networks, distinguished by its capability to process structured data and address the issue of linear separability inherent in traditional models. The MLP employs a fully connected feedforward architecture, wherein the network dynamically learns underlying patterns in the data through the adjustment of weights and biases. Each neuron incorporates an activation function that allows the modeling of complex nonlinear relationships.

To enhance the performance of the MLP model, it is combined with Particle Swarm Optimization (PSO), a metaheuristic optimization algorithm employed to fine-tune the network's weights and biases. This integration contributes to achieving higher prediction accuracy and accelerates the convergence process compared to conventional training methods. The architecture of the model comprises the following key components:

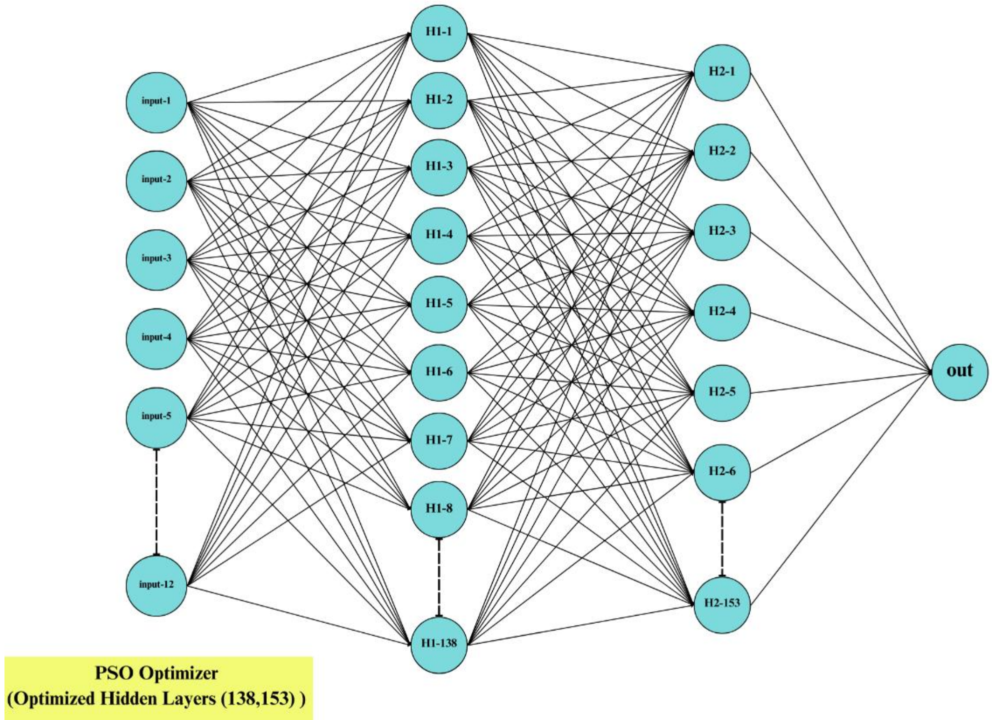

Figure (3.4) MLP with PSO Optimization.

- Input Layer: Processes the input features x_t of the data, where each feature represents an attribute of the dataset. The number of neurons in this layer corresponds to the dimensionality of the input data.
- Hidden Layers: Capture underlying patterns and relationships in the data through weighted transformations and activation functions. Each hidden layer performs the following operation:

$$o = \sum_{i=0}^{N} \beta_i \ . g(\omega_i . x + b_i) \qquad (6)$$

Where:

o The final output of the model.

β_i The weight associated with the i hidden neuron

$g(.)$ the activation function used in the hidden layer

ω_i The weight matrix connecting the input x to the i hidden neuron.

x The input vector to the model.

b_i The bias associated with the i hidden neuron.

N: The number of hidden neurons in the layer.

- Output Layer**:** Maps the final output of the last hidden layer to the target variable. The structure of this layer depends on the type of task:

1. Regression Tasks: Contains a single neuron with a linear activation function.
2. Classification Tasks: Contains one or more neurons with a SoftMax or Sigmoid activation function.

MLPs are highly efficient at processing tabular data, images (via flattening), and other structured datasets due to their ability to represent intricate relationships between features. This architecture is widely used in various applications, including healthcare, predictive analytics, financial modelling, and pattern recognition, making it a cornerstone for solving problems that require accurate predictions and feature interaction analysis.

3.3.4 Model training.

1. Training data: The prepared data is divided into training and validation sets to ensure efficient training and validation of the model. The training set is used to teach the model to recognize patterns in the data, while the validation set is used to monitor the model's performance and avoid overfitting.

2. Optimization: The optimization process relies on algorithms that minimize the loss function to ensure prediction accuracy, where advanced techniques are incorporated to measure how closely the model's predictive distribution matches the true distribution of the data, reflecting the actual desired preferences.

3. Validation: The model's performance is verified on a validation set, which allows the model's accuracy to be evaluated on data it has never seen before. The parameters are tuned iteratively, where the model is further improved based on the observed performance to ensure optimal results.

3.3.5 Evaluation and testing.

To effectively evaluate and test the model, it is recommended to split the data into training and test sets, Appropriate performance indicators such as precision, recall, positive accuracy, and F1 score should be chosen to provide a comprehensive evaluation. Error analysis is also necessary to understand the failure and success cases, which helps in improving the model.

3.3.6 Interpretation of results.

To draw meaningful conclusions about the performance of the system, this step must be able to determine whether the model identifies people with heart failure with high accuracy and whether its performance is satisfactory compared to existing methods or theoretical expectations.

3.3.7 Future Improvements.

1. Increase data accuracy: Improving the quality of data input to the model by collecting more recent and comprehensive data and more diverse data sources can help increase prediction accuracy.
2. Improving Model Performance in Advanced Ways: Experimenting with techniques to improve MLP performance, helping to improve forecast accuracy for critical time periods.
3. Dealing with unbalanced data distribution: In rare diseases such as heart failure, there may be an imbalance between positive and negative case samples and the model can be improved using techniques to address the unbalanced distribution.

3.4 Research Instrument.

In these research studies, the dependent variable is the primary element that researchers seek to measure or predict, as it represents the outcome that is affected by the independent variables. In medical research, especially the study of heart failure, the dependent variable expresses the extent of the occurrence of the disease or the development of the patient's health condition, this variable depends on multiple factors such as age, health condition, and lifestyle, which makes it an important indicator for understanding the relationship between the influencing factors and the potential outcomes, by analyzing the dependent variable, researchers can draw accurate conclusions about the effect of different variables on the development of the health condition.

3.4.1 Dependent variable.

In the available dataset, the dependent variable is heart disease, which expresses the pathological condition related to heart disease, this dependent variable is the main target of the analysis, as the probability of an individual having heart disease is checked based on the effect of other variables.

3.4.2 Independent Variable.

The dataset includes several independent variables, such as Age, Sex, Cholesterol, and MaxHR, which play a role in influencing the dependent variable. These independent variables are used to build predictive models with the aim of analyzing and studying the relationship between different factors and the likelihood of developing heart disease, which contributes to understanding and identifying the factors that influence increasing or decreasing the risk of developing heart disease.

3.5 Conceptual Framework.

The conceptual framework is a basic structure used in research and studies to clarify the relationships between different concepts and variables, The conceptual framework helps to understand how different variables and concepts interact in the context of the study, The conceptual framework forms the basis for building research hypotheses and guiding the analysis and interpretation of results. Figure (3.5) illustrates the conceptual framework.

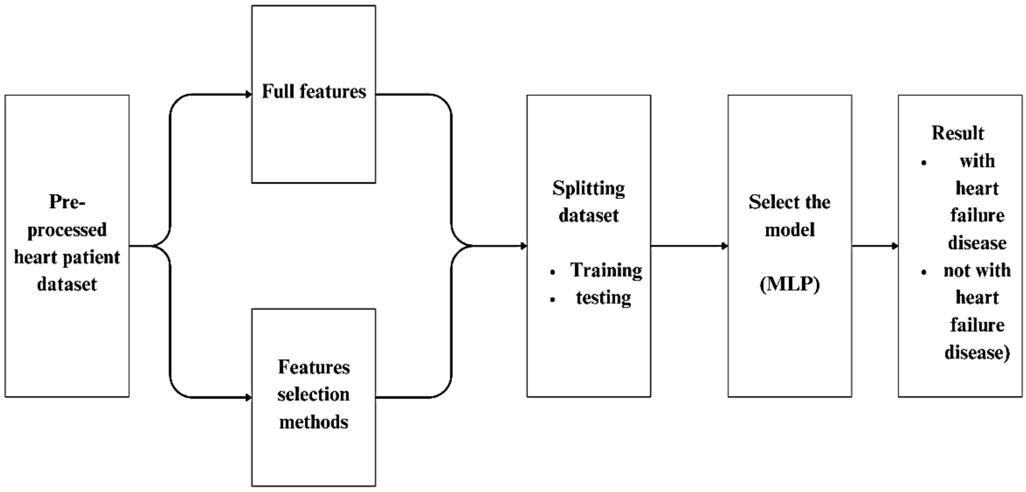

Figure (3.5) Conceptual Framework

MLP was used to develop the heart failure prediction system. The model building process begins with preparing patient data, where the data is processed and purified to ensure its quality and suitability for use in analysis and prediction, this step includes dealing with missing values and ensuring that the data is formatted in a manner that matches the model's requirements, which contributes to the accuracy of the final predictions.

Then comes the feature selection stage, which is an essential step in improving the model's performance and reducing computational complexity All available features in the data can be used, and a set of the most influential features can be selected using feature selection methods This selection depends on the nature of the data and the study objectives, as identifying the most relevant features helps increase the efficiency of the model and improve its accuracy.

Upon completion of data preparation and feature selection, the data is divided into two sets: training and testing This division allows the model to be trained on a set of data, and then its accuracy to be tested on another set that was not used during training, which contributes to verifying the model's performance and its ability to generalize to new data.

The MLP model was chosen as the primary model in this study due to its strong capabilities in handling complex data patterns and its flexibility in modeling non-linear relationships, which aligns well with the nature of patients' health condition data, MLP is one of the effective models for predicting future cases by learning from data and identifying critical patterns.

At the end of the training process, the model gives results showing whether the patient is at risk of heart failure or not. These results allow healthcare providers to make decisions based on the model's accurate predictions, which supports efforts in early detection of heart failure and taking the necessary preventive measures.

3.6 Heart Failure Prediction System.

The MLP (Multilayer Perceptron) Heart Failure Prediction System is an advanced tool designed to predict heart failure based on patient data. The system includes the following elements:

1. Input Data:

i. Demographic Data: Includes characteristics such as age, gender, and weight, which help the MLP model tailor predictions to the specific attributes of each patient.

ii. Medical History: Encompasses the patient's medical history, including symptoms commonly associated with heart conditions. This allows the model to gain insights into the patient’s overall health and generate accurate predictions.

iii. Feature Selection: Key variables are selected from the available data to improve the model's accuracy and efficiency by focusing on factors that have the most significant impact on heart failure, this approach ensures that the MLP model leverages relevant data to effectively analyses patient health and provide reliable heart failure predictions.

2. Algorithmic approach.

i. MLP Model: This model is based on feedforward neural networks that can learn complex relationships between input variables, making it effective for analyzing structured medical data. MLP is used to process patient information and identify patterns that indicate the likelihood of heart failure.

ii. Integration into Deeper Layers: MLP can be designed with multiple hidden layers, enabling the model to handle complex data and learn intricate relationships between variables. This layered architecture enhances the model's ability to provide accurate predictions by capturing non-linear patterns in the data.

3.7 Evaluation.

As mentioned earlier, to effectively evaluate and test the model, it is recommended to split the data into training and test sets, using method to enhance the reliability of the results. Appropriate performance indicators such as precision, recall, positive accuracy, and F1 score should be chosen to provide a comprehensive evaluation. Error analysis is also necessary to understand failure and success cases, which helps in improving the model.

3.7.1 Technologies used.

1. MLP: is a type of feedforward neural network that is highly effective for modeling non-linear relationships in structured data. It consists of multiple layers of interconnected neurons, including input, hidden, and output layers, allowing the model to learn complex patterns and make accurate predictions.
2. PSO: is an optimization technique inspired by the social behavior of particle swarms. It is used to optimize hyperparameters and feature selection for MLP models, improving their performance by finding optimal configurations through iterative updates of particle positions in the solution space.
3. Accuracy Score: is a metric used to evaluate the overall performance of a classification model by calculating the proportion of correct predictions out of the total number of predictions. It is a straightforward measure of model effectiveness.
4. Classification Report: provides a detailed summary of the model's performance, including precision, recall, F1-score, and support for each class. This helps evaluate the model's strengths and weaknesses in handling different classes.
5. Confusion Matrix: is a visualization tool that shows the true positive, true negative, false positive, and false negative counts for a classification model. It provides insights into the types of errors the model is making and helps in fine-tuning it.

6. ROC: is a graphical representation of a classification model’s ability to distinguish between classes by plotting the true positive rate against the false positive rate at various threshold levels.
7. AUC: is a metric derived from the ROC curve that measures the model's overall ability to classify positive and negative instances. A higher AUC indicates better performance in distinguishing between classes.

3.7.2 Evaluation steps.

1. Splitting the Data into Training and Testing: Divide the dataset into a training set and a testing set. The training set is used to train the MLP model, while the testing set evaluates the model’s performance on unseen data. This ensures a clear separation between training and evaluation stages.
2. PSO for Optimization: Use PSO to optimize the hyperparameters of the MLP model, such as the number of layers, neurons per layer, learning rate, and activation functions. PSO searches for the best parameter configuration, improving the model's overall performance and efficiency.
3. Accuracy Measure: Use the accuracy score metric to calculate the proportion of correct predictions made by the model, compute the average accuracy to provide a comprehensive measure of the model’s ability to classify correctly.
4. Confusion Matrix: Generate a confusion matrix to analyze the model’s classification performance. The matrix displays the counts of true positives, true negatives, false positives, and false negatives for each class, helping identify areas where the model may be underperforming.

5. Classification Report: Produce a classification report containing metrics such as Precision, Recall, F1-Score, and Support for each class. This detailed breakdown highlights the model's strengths and weaknesses in predicting specific classes.
6. Calculate the AUC-ROC Curve: Plot the ROC curve to visualize the trade-off between true positive rate (sensitivity) and false positive rate at different thresholds. Use the AUC (Area Under the Curve) as a summary metric to evaluate the model's ability to distinguish between classes effectively.

3.7.3 Final Evaluation.

It shows whether the model has good performance in prediction. If it achieves high accuracy when tested on unseen data, this indicates its ability to distinguish between classes effectively. Using the confusion matrix, it is possible to determine the number of correct and incorrect predictions for each class, allowing for a detailed analysis of the quality of common errors. High AUC and ROC values also demonstrate the model's reliable ability to distinguish between classes accurately.

Additionally, performance measures such as precision, sensitivity (recall), and F1-Score reveal a balance in predictions across different classes, enhancing the model's reliability and fairness in handling class imbalances. The classification report provides a comprehensive overview of these metrics, supporting a deeper understanding of the model's strengths and weaknesses.

All these performance indicators confirm the effectiveness of the MLP model, making it suitable for predicting heart failure and ensuring reliable and accurate outcomes.

3.7.4 The Outcome.

The evaluation results of the MLP model are expected to achieve good performance in prediction, as the model is capable of correctly classifying most cases. The ROC curve and AUC values reflect the model's ability to effectively distinguish between different classes, indicating a high level of accuracy in prediction. The confusion matrix will demonstrate the model's ability to correctly predict positive and negative cases, with a limited number of errors.

The classification report will show a good balance between accuracy and sensitivity, detecting the majority of positive cases while minimizing false alarms. This highlights the model's reliability in making balanced predictions across different classes. Metrics such as accuracy score further validate the model's overall performance and its ability to generalize effectively to unseen data.

The following figure (3.4) shows the difference between the improved model using PSO, which optimizes the parameters of the MLP model before training. By applying PSO, the model achieves better parameter configurations, enhancing its predictive power and accuracy. PSO also helps to improve the model's ability to fairly classify all classes, even in scenarios where there is a significant imbalance in the dataset.

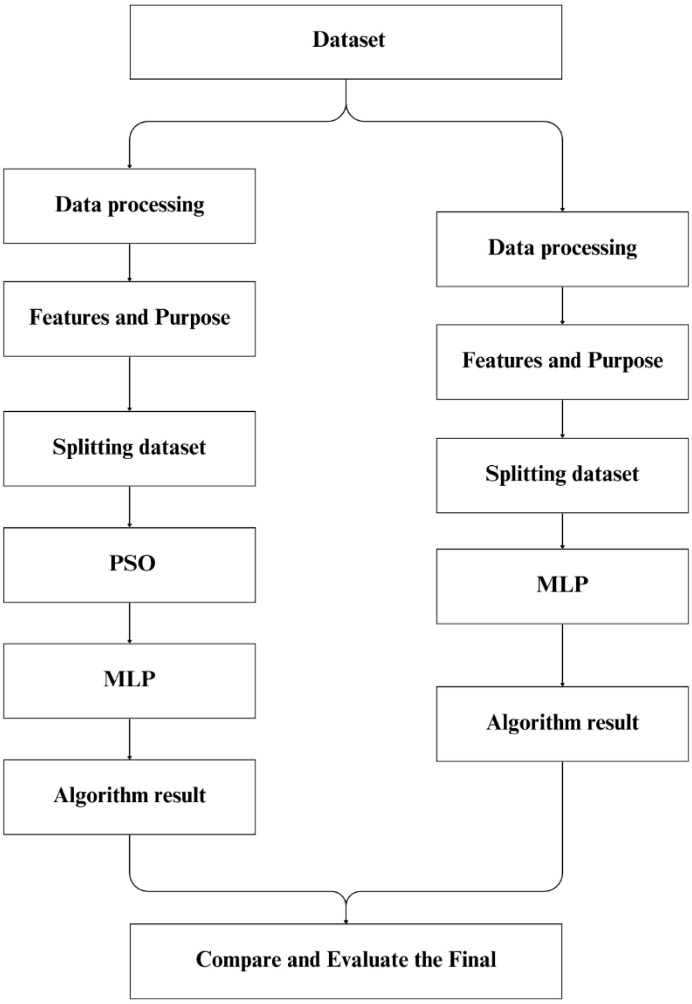

Figure (3.6) Model performance comparison chart.

After optimizing the MLP model using PSO, the model demonstrates enhanced performance, particularly in metrics such as Recall and F1-Score, which reflect its ability to detect underrepresented classes while maintaining a low false alarm rate. This improvement ensures the model's reliability for practical applications related to heart failure prediction.

The basic right model without optimization treats the data as is, without any adjustment or optimization for class balance. If the original data has an imbalance in the distribution between classes, such as having a large number of samples for a particular class versus a small number for another class, the MLP model is trained on this imbalanced data. As a result, the model is biased towards the most common class and performs poorly in predicting the less represented class. Although the overall accuracy may appear high, this result is misleading because the model actually fails to correctly predict the less represented classes. Metrics such as recall and F1-score are often poor in this case.

In contrast, the left model optimized using PSO is the better choice when the original data has an imbalanced distribution of classes. PSO optimizes the parameters of the MLP model, such as weights and biases, to enhance its performance and address the class imbalance issue. By selecting the most critical features and finding optimal configurations, the model ensures improved accuracy and fairness across all classes.

The basic right model is more appropriate when the classes are already balanced or when the imbalance problem is not a significant challenge. However, when dealing with imbalanced data, using PSO with the MLP model leads to more accurate and reliable predictions, especially for the less represented classes, ensuring a balanced and fair performance for all classes.

Chapter IV
Results And Discussion.

With technological advancements and increased reliance on data, data analysis has become essential in scientific research and evidence-based decision-making. Data analysis aims to extract knowledge from raw data using systematic techniques that help explain phenomena and understand complex relationships. In academic and medical fields, data analysis supports improving the accuracy of results, testing hypotheses, and developing models that contribute to improved diagnosis and treatment, as well as identifying factors affecting public health.

4.1 Data Analysis.

It is a fundamental process that aims to extract information and patterns from available data to support decision-making and understand various phenomena. Medical data is one of the most important types of data that are subject to analysis, as it can provide valuable insights that help improve healthcare and diagnose diseases more accurately.

By analyzing medical data, such as that related to heart disease, it is possible to identify factors affecting patients' health, discover patterns associated with disease, and design effective strategies for medical intervention in this context, which contains information such as age, gender, cholesterol level, and blood pressure, a powerful tool that can be used to apply advanced analysis methods and generate accurate predictions about the health status of individuals.

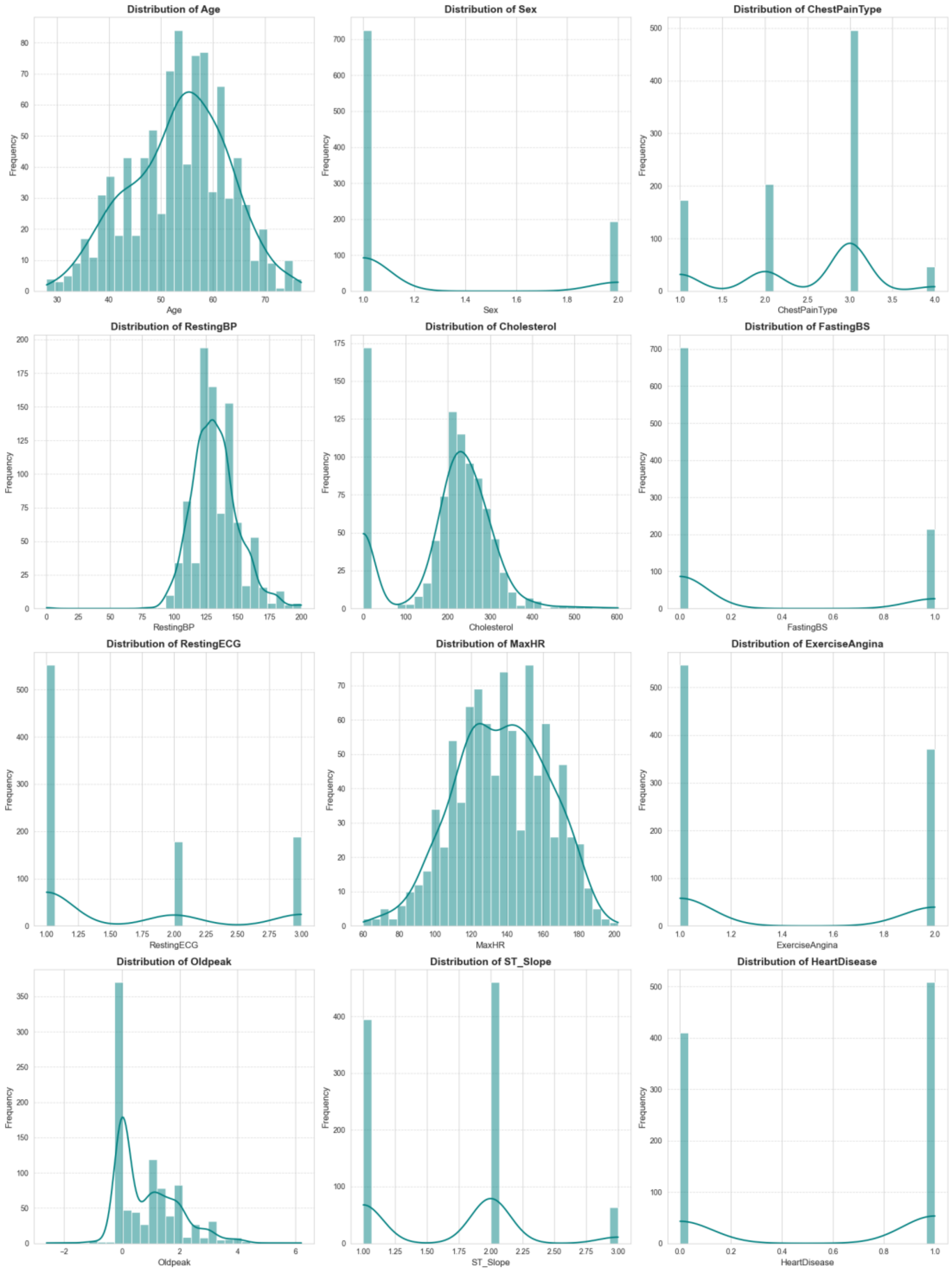

Figure (4.1) Heart patient data distribution.

Figure (4.1) contains a data set used with probability density lines (KDE) that display the data distribution for each variable in a data set related to heart disease. Each graph represents a specific variable and displays the number of times the different values of this variable occur.

1. Age distribution: The horizontal axis represents age (Age) and the vertical axis represents the number of individuals in each age group. It is noted that the distribution is close to the normal distribution, as most values are concentrated between 40 and 65 years, and values less than 30 or greater than 70 are relatively rare. The blue curved line represents the distribution density estimate (KDE), and shows that the most common values fall around 50-55 years, i.e. mostly on patients in middle age or older, which is expected because heart disease is more common with age.

2. Gender distribution: The horizontal axis contains two values, 1 symbolizes males and 2 symbolizes females. There is a clear difference in the number of individuals between the sexes, as most of the sample is male and there may be a bias in the sample or that men are more susceptible to heart disease than women.

3. ChestPainType Distribution: This variable is categorical, it has values 1, 2, 3, 4 and some categories are more common than others. The elevations in the distribution indicate that some types of chest pain are more common. There are different types of chest pain, some of which may be a strong indicator of heart problems such as angina, while some may be unrelated to the heart.

4. Resting Blood Pressure Distribution: The distribution looks like a normal distribution but is slightly skewed. Most values range between 100-140 mmHg, which is the normal or slightly high range for blood pressure there are some cases

that record very high values (over 180) and others that record very low values (below 90). High blood pressure can be a major risk factor for heart disease, so it is important to analyze its relationship with the HeartDisease variable.

5. Cholesterol Distribution: The distribution appears skewed to the right, meaning that some individuals have very high cholesterol levels (more than 400 mg/dL). Most values fall between 150-300 mg/dL. Also, high cholesterol is a very strong risk factor for heart disease.

6. Fasting Blood Sugar Distribution: This variable is binary, where 0 is normal blood sugar and 1 is high blood sugar and most individuals have normal levels, while a smaller percentage have high levels and high fasting blood sugar may be associated with diabetes, which is a major risk factor for heart failure.

7. Resting ECG Distribution: This variable is categorical and contains the values 0 normal 1 slight disturbance 2 major disturbance and most individuals have normal readings, but there are a fair number of them who have disturbances and ECG results that may be an indication of heart problems such as a heart attack or an irregular heartbeat.

8. Distribution of maximum heart rate: The distribution appears to be approximately normal with most values ranging between 100-180 beats/min, with a peak around 140-160. There are a few cases with very low or very high values. Heart rate during exercise is an important indicator of cardiac fitness, and may be associated with the risk of heart disease.

9. Distribution of exercise-induced angina: A binary variable appears: 0 does not suffer from angina during exercise 1 suffers from angina during exercise The vast majority do not suffer from angina during exercise, while there is a smaller group that suffers from it. Patients who suffer from angina during exercise may have narrowing of the coronary arteries, which increases the risk of coronary heart disease.

10. ST-segment depression distribution: Most values are centered around zero, but a few individuals have high values. The higher this index, the more likely there is myocardial ischemia. High Oldpeak values may indicate myocardial ischemia resulting from coronary artery disease.

11. ST-segment slope distribution: The ST-segment slope (ST_Slope) distribution shows three main patterns, namely Downsloping, Flat, and Upsloping, which reflect the heart's response to stress during exercise. The downward pattern is a strong indicator of myocardial ischemia and is associated with a high risk of heart disease, while the flat pattern indicates an intermediate risk that requires close monitoring. In contrast, the upward pattern is considered a normal sign indicating a lower risk of heart disease. Due to the importance of this variable in diagnosis, it is widely used along with other variables such as chest pain, angina during exercise, and Oldpeak levels, making it a crucial factor in building predictive models for early detection of coronary heart disease.

12. Heart Disease Distribution: Binary variable: 0 does not have heart disease 1 has heart disease There is a large number of patients with heart disease, indicating that

the sample contains a high percentage of positive cases. This is the target variable in prediction models, and it will be useful to analyze its relationship with the rest of the variables.

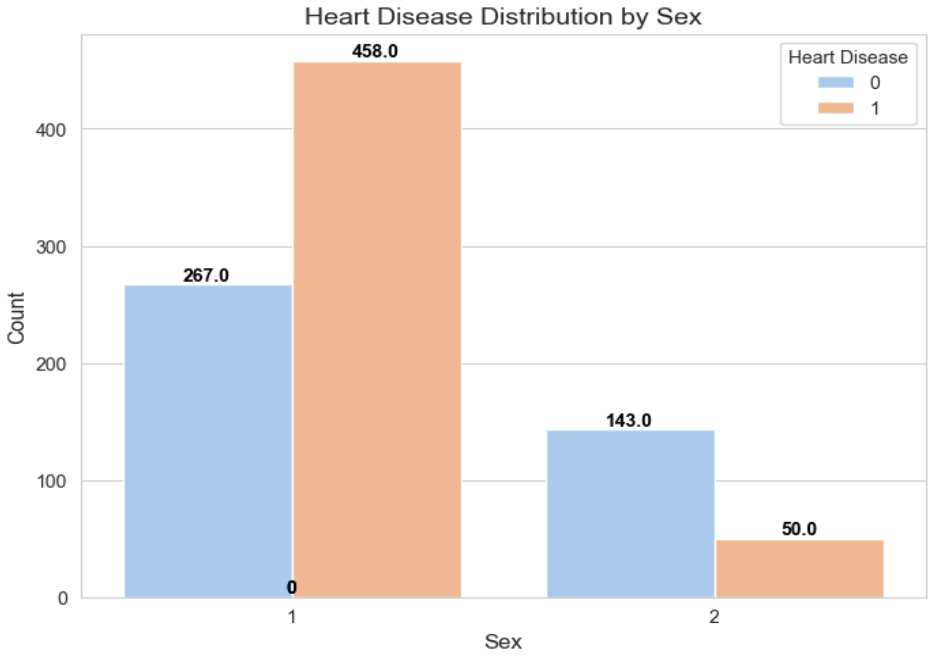

Figure (4.2) Distribution of heart disease by gender.

Figure (4.2) shows the distribution of heart disease by gender, where it is clear that males are more susceptible to heart disease than females. The number of males with heart disease is 458 cases, which is much greater than the number of non-infected, which reaches 267 cases, while the number of infected females does not exceed 50 cases compared to 143 non-infected cases. This disparity may be attributed to biological factors such as the effect of testosterone, which may increase the risk of infection, while estrogen in women provides a protective effect on the heart. Behavioral factors also play an important role, as men are more susceptible to unhealthy lifestyles such as smoking, lack of exercise, and exposure to high psychological stress, which increases the likelihood of heart disease. In addition, high blood pressure and high cholesterol are more common among men, which contributes to their higher rates of infection. Prevention plays a crucial role in reducing this gap, by improving lifestyle, monitoring health factors such as blood pressure, sugar levels, and cholesterol, in addition to reducing stress and psychological pressure.

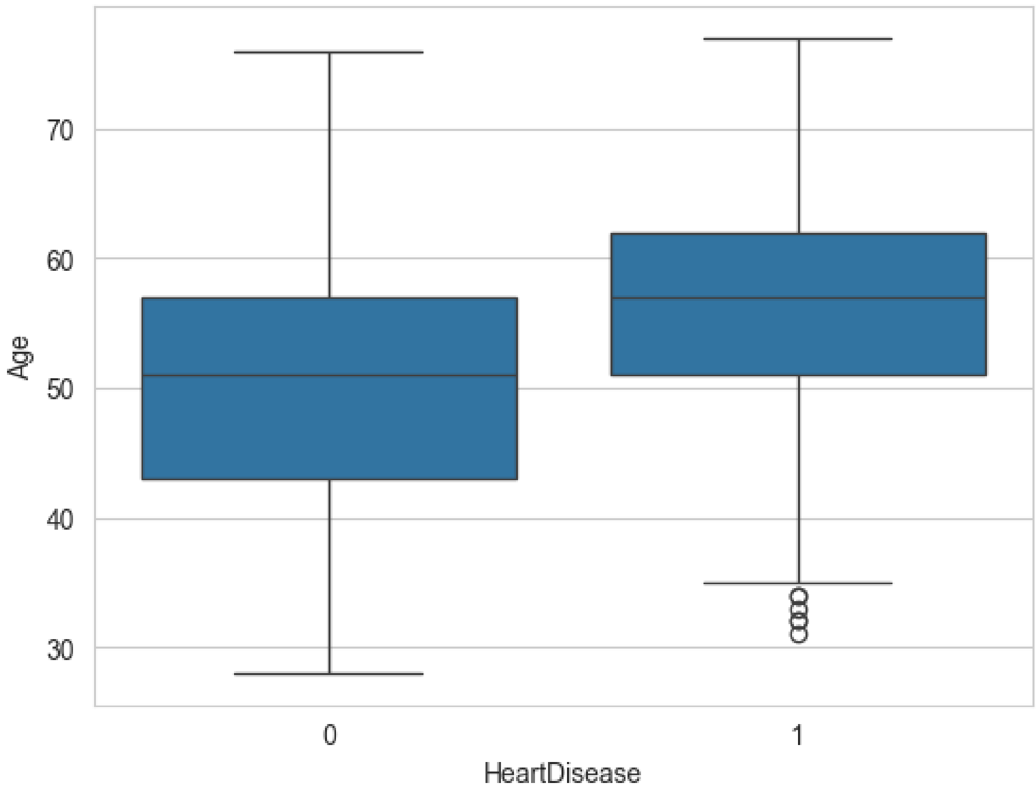

Figure (4.3) Age distribution by incidence of heart failure disease

Figure (4.3) represents the age distribution of individuals with and without heart failure disease, The horizontal axis shows the two categories of heart disease (HeartDisease), where "0" represents individuals without heart disease, and "1" represents individuals with heart disease, while the vertical axis represents age

(Age). It is clear that individuals with heart disease tend to be older than those without heart disease, as the median age of those with heart disease is higher than the median age of those without heart disease. The age distribution in the affected category extends to values less than 40 years with some extreme values, indicating that there are some younger individuals who suffer from the disease, but at a lower rate. On the other hand, the shape of the non-affected category shows that their age range is slightly lower, as the majority are under the age of 60 years. This analysis indicates that advancing age is associated with an increased risk of heart disease, which is consistent with the medical literature that confirms that aging leads to deterioration of vascular health and an increase in risk factors such as high blood pressure and atherosclerosis.

Table (4.1) Descriptive statistics for the heart disease dataset.

Feature	Count	Mean	Std Dev	Min	25%	50%	75%	Max
Age	918	53.51	9.43	28.0	47.0	54.0	60.0	77.0
Sex	918	1.21	0.41	0.0	1.0	1.0	1.0	1.0
ChestPainType	918	2.45	0.85	1.0	2.0	2.0	3.0	4.0
RestingBP	918	132.4	18.51	0.0	120.0	130.0	140.0	200.0
Cholesterol	918	198.8	109.38	0.0	173.25	223.0	267.0	603.0
FastingBS	918	0.23	0.42	0.0	0.0	0.0	0.0	1.0
RestingECG	918	1.6	0.81	0.0	1.0	1.0	2.0	2.0
MaxHR	918	136.81	25.46	60.0	120.0	138.0	156.0	202.0
ExerciseAngina	918	1.4	0.49	1.0	1.0	1.0	2.0	2.0
Oldpeak	918	0.89	1.06	-2.6	0.0	0.6	1.5	6.2
ST_Slope	918	1.63	0.67	0.0	1.0	2.0	2.0	2.0
HeartDisease	918	0.55	0.49	0.0	0.0	1.0	1.0	1.0

Table (4.1) shows a statistical table of a set of descriptive statistics for variables related to heart disease, based on data from 918 patients for all patients with and without heart disease, The table includes information about the mean, standard deviation (std), minimum and maximum values (min), and quartiles (25%, 50%, 75%) for each variable.

Age analysis indicates that the average age of patients is 53.5 years, with a minimum of 28 years and a maximum of 77 years, reflecting that heart disease is more common among middle-aged and elderly people. As for gender, the mean is 1.21, indicating that the sample contains a larger number of males (1) than females (2).

The distribution of resting blood pressure (RestingBP) shows a mean of 132.4 mmHg with a standard deviation of 18.5, indicating that there are many cases of high blood pressure. Cholesterol has a mean of 198.8 mg/dL and a maximum of 603 mg/dL, indicating that some individuals have very high cholesterol levels, which may be a major risk factor for heart disease.

Fasting blood sugar (FastingBS) shows that 23.3% of patients have high blood sugar levels, reflecting its association with diabetes as an important risk factor. The average maximum heart rate (MaxHR) is 136.8 beats/min, an indicator of heart health and physical fitness.

As for exercise-induced angina, about 40% of patients suffer from it, indicating potential problems with blood flow to the heart during physical activity. ST segment depression (Oldpeak), which is an indicator of myocardial ischemia, ranges from -2.6 to 6.2, with higher values indicating an increased risk of heart problems.

Finally, the heart disease variable shows that 55.3% of the sample had heart disease, indicating that the sample contains a high proportion of patients compared to those without, which highlights the importance of other variables in building an effective predictive model for detecting heart disease.

Table (4.2) Descriptive statistics of the affected heart disease dataset.

Feature	Count	Mean	Std Dev	Min	25%	50%	75%	Max
Age	508	55.9	8.73	31.0	51.0	57.0	62.0	77.0
Sex	508	1.1	0.3	1.0	1.0	1.0	1.0	1.0
ChestPainType	508	2.83	0.58	1.0	3.0	3.0	3.0	4.0
RestingBP	508	134.18	19.83	0.0	120.0	132.0	145.0	200.0
Cholesterol	508	175.94	126.39	0.0	0.0	217.0	267.0	603.0
FastingBS	508	0.33	0.47	0.0	0.0	0.0	1.0	1.0
RestingECG	508	1.65	0.8	0.0	1.0	2.0	2.0	2.0
MaxHR	508	127.66	23.39	60.0	112.0	126.0	144.25	195.0
ExerciseAngina	508	1.62	0.49	1.0	1.0	2.0	2.0	2.0
Oldpeak	508	1.72	1.15	-2.6	1.0	1.6	2.6	6.2
ST_Slope	508	1.94	0.5	1.0	1.0	2.0	2.0	3.0
HeartDisease	508	1.0	0.0	1.0	1.0	1.0	1.0	1.0

This table (4.2) presents a table of descriptive statistics for a dataset related to heart disease risk factors, which includes several variables such as age, gender, type of chest pain, resting blood pressure, and cholesterol level. This analysis helps in understanding the distribution of data and detecting any patterns or outliers.

Number of values Each variable contains 508 samples, which indicates that the data is complete for the affected people without the unaffected people and the arithmetic mean across the median from the central value for each variable where the average age of the sample is 55.9 years, while the average maximum heart rate (MaxHR) is 127.66 beats per minute. These values help in understanding the general distribution of the clinical characteristics of the patients.

Standard deviation (Std): The standard deviation shows the extent of dispersion of values around the mean. For example, the standard deviation for age is 8.73, which indicates that the ages of the patients are distributed within a moderate range around the mean.

Min, Max: These values specify the range that each variable falls within. For example, age ranges from 31 to 77 years, while cholesterol ranges from 0 to 603. A value of 0 in the cholesterol variable indicates that there may be incorrect or missing data, which requires further investigation.

Quartiles (25%, 50%, 75% Quantiles): These values reflect how the data is distributed across quartiles. For example, the first quartile for age is 51 years, the median (second quartile) is 57 years, while the third quartile is 62 years. This indicates that half of the sample falls within this range, which helps us understand the distribution of the data more deeply.

Dependent variable (HeartDisease): All values in this variable appear to be 1, which means that the data relate to patients who have already been diagnosed with heart disease, as mentioned above.

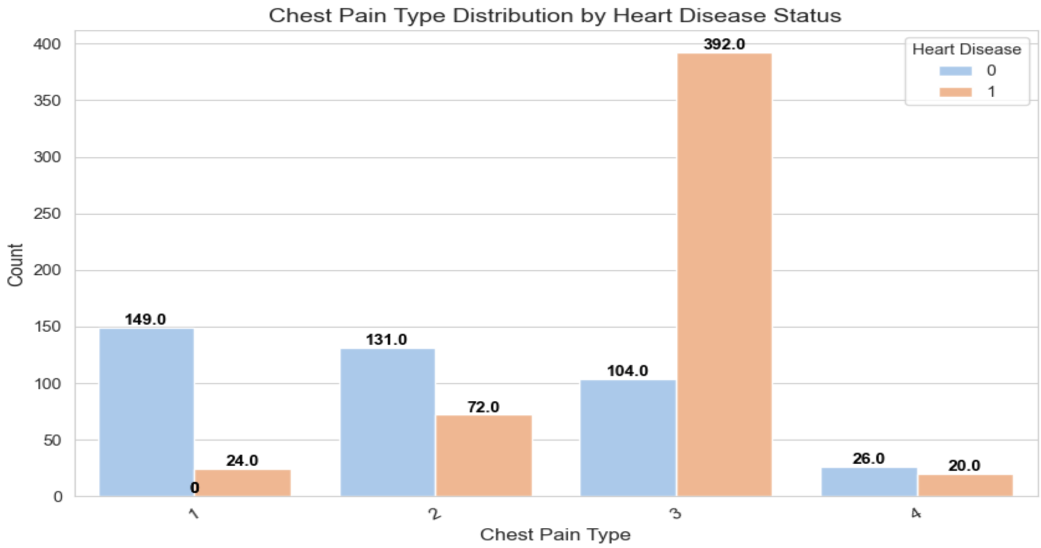

Figure (4.4) Chest Pain Type Distribution by Heart Disease Status.

Figure (4.4) shows the distribution of chest pain types (Chest Pain Type) between individuals with and without heart disease. Chest pain is classified into four types, and the horizontal axis shows the type of chest pain, while the vertical axis represents the number of individuals in each category. The blue bars represent individuals without heart disease (heart disease = 0), while the orange bars represent individuals with heart disease (heart disease = 1).

It is clear that the third type of chest pain (3) is the most associated with heart disease, as there are 392 patients with this category, compared to 104 people without heart disease. In contrast, the first type (1) of chest pain appears commonly in those without heart disease, as their number is 149 people, while only 24 people with heart disease. As for the second type (2), it is distributed more evenly, as there are 131 people without heart disease compared to 72 people with heart disease. As for the fourth type (4), there are 26 people without heart disease and 20 people with heart disease, indicating that there is no significant difference between the two groups.

Type 3 chest pain is strongly associated with heart disease, meaning it may be a strong indicator of risk. Type 1 chest pain is more common among non-heart patients and may indicate pain unrelated to heart disease, such as muscle or gastrointestinal pain. Other types have a mixed distribution, suggesting they may be related to other diseases or different health conditions.

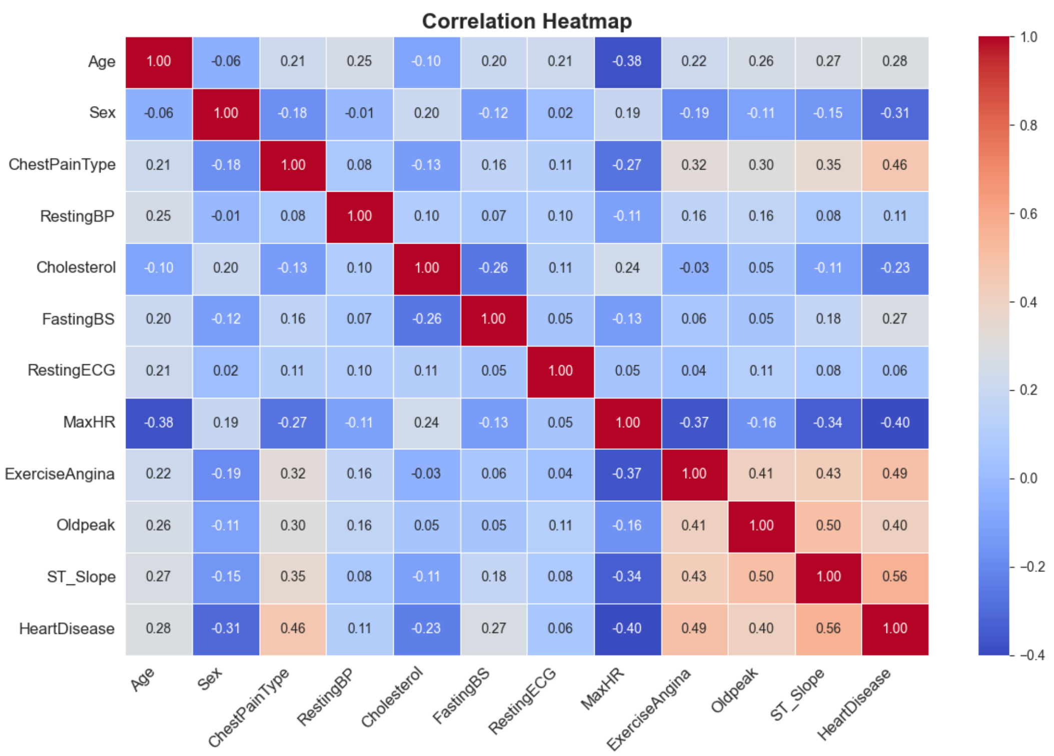

Figure (4.5) Correlation Heatmap of Heart Disease Features.

Figure (4.5) Correlation Heatmap Analysis of Variables and Their Effect on Heart Disease This chart shows the correlation matrix between the different variables in the data set, where the Pearson Correlation Coefficient is used to measure the relationship between each two variables. Values close to 1 or -1 indicate a strong correlation, while values close to 0 indicate no correlation And the correlation analysis with the variable "HeartDisease" which is the targeted variable and we notice the highest values correlated with it.

1. ST_Slope (correlation: 0.56) : The strongest positive association with heart disease, meaning that the slope of the ST segment on the ECG has a significant relationship with the prognosis of the disease.
2. ExerciseAngina (correlation: 0.49): Patients who experience angina during exercise have a higher risk of heart disease.
3. ChestPainType (correlation: 0.46): shows that the type of chest pain can be an important indicator of heart disease, with some types, such as pain associated with angina, being a serious indicator.
4. Oldpeak (correlation: 0.40): Indicates that an increase in Oldpeak (which represents ST depression after exercise) is associated with an increased risk of heart disease.
5. MaxHR (correlation: -0.40): There is a negative correlation, meaning that people with a higher maximum heart rate have a lower risk of heart disease.
6. Sex (correlation: -0.31): The negative correlation indicates that males (1) have a higher infection rate compared to females (2), supporting the previous analysis on the effect of gender on infection rate.

7. Cholesterol (correlation: -0.23): The correlation is weak and negative, indicating that cholesterol alone is not a strong predictor of heart disease in this sample.
8. Analysis of other correlations between variables indicates that there is a strong correlation between ST_Slope and Oldpeak (0.50), indicating that changes in the ST segment during exercise are associated with ST depression. The correlation between Exercise Angina and Oldpeak (0.41) indicates that angina during exercise often leads to ST depression. There is a negative correlation between MaxHR and age (-0.38), indicating that maximum heart rate decreases with age.

4.2 **Model result.**

To more thoroughly analyze the model's performance, the dataset was split into training and test data using varying ratios, as previously mentioned, to study the effect of test data size on prediction accuracy using the MLP algorithm. The results showed that the best performance was achieved when using a 10% test and 90% training ratio, with the model achieving the highest levels of accuracy and stability. Accordingly, the focus was on analyzing the results at this ratio in more detail using evaluation metrics such as precision and recall, as well as confusion matrix analysis to identify sources of error and improve the model's understanding of data behavior.

4.2.1 **Optimized Confusion Matrix**.

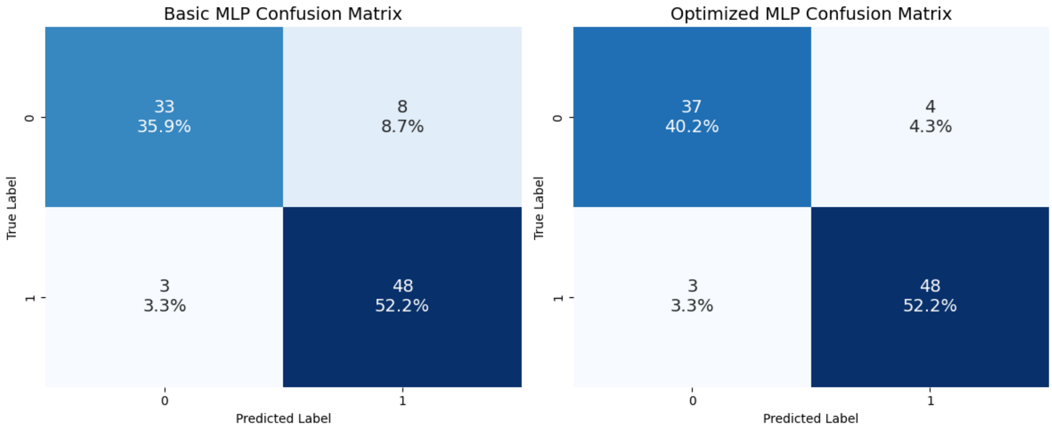

Figure (4.6) Optimized Confusion Matrix for Heart failure Disease Prediction

Figure 4.6 represents the confusion matrices for the baseline and optimized multilayer neural network (MLP) model. The confusion matrix is an important statistical tool for evaluating the performance of classification models, as it shows the distribution of correct and incorrect predictions across different classes.

The left part of Figure 4.9 shows the confusion matrix for the baseline model. The model correctly classified 33 cases as not suffering from heart failure (True Negatives) and correctly identified 48 cases with heart failure (True Positives). However, the model misclassified 8 cases without heart failure (False Positives) and failed to detect 3 cases with heart failure (False Negatives). These results reflect the model's good performance, as most cases were correctly classified.

The right part of the figure shows the confusion matrix for the optimized model. The model improved its performance by correctly classifying 37 cases as true negatives, while maintaining the same number of correctly classified infected cases (48). The number of false positives also decreased to only 4, while the number of missed cases remained the same (3). This improvement reflects the improved model's ability to increase specificity by reducing false positives.

The comparison shows that the optimization process positively impacted the model's performance, particularly in terms of reducing misdiagnoses of healthy individuals, which is important in medical models to avoid unnecessary procedures. At the same time, the model maintained its high sensitivity by being able to detect most actual infected cases, which is essential to avoid missing critical cases in need of medical care.

4.2.2 ROC (Receiver Operating Characteristic) curve.

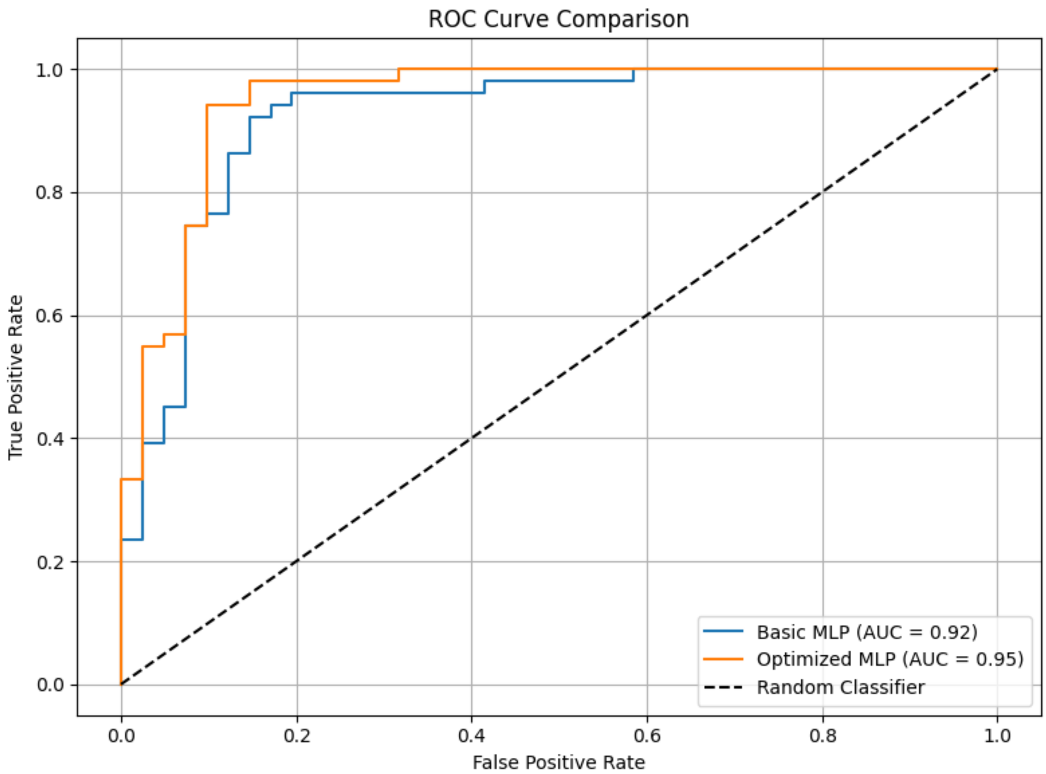

Figure (4.7) ROC_AUC curve analysis of the model.

The ROC curve is a tool for evaluating classification models by analyzing the relationship between the True Positive Rate (TPR) and the False Positive Rate (FPR). The curve shows the model's performance compared to a random classifier, with greater deviation from this line indicating better model performance.

AUC Analysis: The image shows that the area under the curve (AUC) for the baseline MLP model was 0.92, while it increased to 0.95 after the model was optimized. This means that the optimized model is able to distinguish between infected and uninfected individuals with 95% accuracy across various threshold values, reflecting a clear improvement in performance after the optimization process.

Interpretation of Model Performance: When the AUC value approaches 1.0, the model achieves perfect classification without errors, while an AUC value close to 0.5 indicates that the model is making random guesses without actually distinguishing between classes. An AUC value between 0.8 and 0.9 indicates strong predictive performance, while values above 0.9 reflect excellent classification ability. Therefore, the improved model in this study has excellent classification performance in distinguishing between patients with and without heart failure.

4.2.3 Model Classification Report Using Statistical Metrics.

This report in table (4.3) and (4.4) demonstrates the performance of two infection classification models before and after optimization using the molecular swarm optimization (PSO) algorithm. The models were tested on 92 samples using accuracy metrics such as precision, recall, and F1 score to evaluate performance. The baseline model achieved an overall accuracy of 88.04%, while the improved model demonstrated a higher accuracy of 92.39%, indicating significant improvement in predictive ability. For the uninfected class (class 0), the improved model achieved an accuracy of 0.925, a recall of 0.902, and an F1 score of 0.9136. For the infected class (class 1), the accuracy reached 0.923, a recall of 0.941, and an F1 score of 0.932. The overall mean and weighted mean values also showed significant improvements after optimization, rising to approximately 0.92 compared to 0.88 in the baseline model. These results reflect the balanced and robust performance of the improved model, with a high ability to distinguish between infected and uninfected cases.

Table (4.3) Basic MLP Classification Report

Class	Precision	Recall	F1-Score	Support
0	0.9167	0.8049	0.8571	41
1	0.8571	0.9412	0.8972	51
Accuracy			0.8804	92
Macro Average	0.8869	0.8730	0.8772	92
Weighted Average	0.8837	0.8804	0.8793	92

Table (4.4) Optimized MLP (PSO) Classification Report.

Class	Precision	Recall	F1-Score	Support
0	0.9250	0.9024	0.9136	41
1	0.9231	0.9412	0.9320	51
Accuracy			0.9239	92
Macro Average	0.9240	0.9218	0.9228	92
Weighted Average	0.9239	0.9239	0.9238	92

The results obtained by varying the split of the training and test data and comparing the performance of both the basic MLP model and the model optimized using particle optimization (PSO) showed a significant superiority of the improved model across all data split ratios between training and testing. The highest accuracy level using the improved model reached 92.39% when the data was split 90% for training and 10% for testing, compared to only 88.04% for the basic model at the same split ratio. It is noteworthy that the PSO algorithm improved not only accuracy but also other performance indicators such as precision, recall, and harmonic measure (F1-Score), demonstrating its ability to more effectively balance the classification of different classes.

table (4.5): Summary of MLP and Optimized MLP (PSO) Metrics

Training : Testing Ratio	Model	Accuracy	Precision (avg)	Recall (avg)	F1-Score (avg)
90:10	Basic	0.8804	0.8869	0.8730	0.8772
	Optimized	0.9239	0.9240	0.9218	0.9228
85:15	Basic	0.8696	0.8733	0.8638	0.8668
	Optimized	0.9058	0.9070	0.9026	0.9043
80:20	Basic	0.8587	0.8641	0.8510	0.8548
	Optimized	0.8967	0.9004	0.8913	0.8945
75:25	Basic	0.8478	0.8574	0.8384	0.8428
	Optimized	0.9000	0.9011	0.8966	0.8984
70:30	Basic	0.8333	0.8435	0.8226	0.8272
	Optimized	0.8986	0.8979	0.8965	0.8972
65:35	Basic	0.8758	0.8767	0.8717	0.8736
	Optimized	0.8913	0.8940	0.8864	0.8891
60:40	Basic	0.8125	0.8161	0.8040	0.8072
	Optimized	0.8777	0.8773	0.8748	0.8759
55:45	Basic	0.8213	0.8255	0.8130	0.8163
	Optimized	0.8720	0.8718	0.8687	0.8700

Furthermore, the results revealed a direct relationship, as shown in Table (4.3), between the percentage of training data reserved for the model and the quality of the results. The performance of both models gradually improved as the percentage of training data increased. However, the improved model maintained its superiority at all stages. From this study, it can be concluded that combining evolutionary optimization algorithms such as PSO with neural network models effectively contributes to improving classification accuracy, especially in critical applications such as medical classification.

Chapter V
Conclusions And Recommendations.

5.1 Conclusions.

The model demonstrated high efficiency in classifying individuals with and without heart disease, exhibiting a strong ability to detect positive cases (patients), However, its performance in identifying non-affected individuals requires improvement, as the recall value for this category was 0.87, which is lower compared to the other category. This indicates the potential for some misclassifications of non-affected individuals.

Moreover, the model achieved high levels of sensitivity and specificity, making it well-suited for medical applications that demand accurate predictions. High sensitivity reflects the model’s ability to detect most disease cases, while high specificity indicates its effectiveness in correctly excluding non-affected individuals. However, balancing these two metrics is crucial, especially in clinical settings where misclassification errors can have significant medical consequences.

5.2 Recommendations

To enhance the model's performance, the following strategies are recommended:

1. Threshold tuning: Determining the optimal decision threshold to balance between improving patient detection rates (recall) and reducing misclassifications, including false positives that may lead to unnecessary medical procedures and false negatives that may result in undiagnosed cases.

2. Data rebalancing: Applying techniques such as synthetic data redistribution or sampling methods to ensure a more balanced distribution of classes, thereby minimizing bias from imbalanced datasets.
3. Enhancing classification algorithms: Optimizing model parameters using techniques such as grid search or random search to improve predictive performance.
4. Ensemble learning integration: Leveraging ensemble learning techniques, such as bagging and boosting, to enhance predictive accuracy and increase model reliability.
5. Additional testing: Evaluating the model using diverse datasets to ensure its generalizability across different clinical environments and improve prediction accuracy.
6. Utilizing IoT technologies: Employing smart sensors and Internet of Things (IoT) technologies to collect real-time health data, thereby enhancing prediction accuracy and improving remote patient monitoring for faster and more precise medical responses.

Implementing these recommendations will contribute to improving the model's performance and achieving higher accuracy in predicting heart disease cases, thereby supporting more precise and effective medical decision-making.

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