جمهورية العراق

وزارة التعليم العالي
والبحث العلمي جامعة

جامعة ديالى

كلية العلوم

كشف شذوذ ضربات القلب باستخدام

تقنيات التعلم العميق

رسالة

مقدمة الى قسم علوم الحاسوب / كلية العلوم/ جامعة ديالى وهي جزء من متطلبات نيل درجة الماجستير في علوم الحاسوب

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Chapter one

General Introduction

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General Introduction

1.1 Introduction

The primary focus of medical development is centered on people, recognizing their fundamental right to lead healthy lives in harmony with nature. Regrettably, the persistently high mortality rates associated with debilitating diseases, particularly heart diseases, pose a significant challenge. These high mortality rates extend to a range of conditions, including diseases of:

- Diseases of the skeletal system.
- Cardiovascular diseases.
- lung diseases.
- Neurological diseases and others.

Most of these diseases with increasing age require periodic examinations and the provision of modern tools for health monitoring. Promoting and developing early diagnosis of diseases by integrating information and communications technology into the health care system [e-health]

Heart disease kills about 17.9 million people yearly, 31% of all deaths worldwide. Cardiovascular disease is now the top cause of death and a serious threat to people's health. Electrocardiograms (ECGs) are the most common way to determine if someone has heart problems. Surface electrodes can record the ECG data, which shows how the heart's electrical activity changes during each heartbeat. By analyzing ECG signals, doctors can get important information about a patient's health and quickly spot cardiac problems, saving lives and improving the quality of life with the right care[1].

Classification of the (ECG) is one of the effective and highly efficient methods for detecting heart diseases, which helps diagnose most heart-related symptoms. The medical staff is overburdened and may make mistakes due to work pressure, and the ECG diagnosis depends on their judgment. ECG automatic analysis will help medical professionals. ECG detection is the most effective and straightforward method. Doctors use manual detection and ECG analysis to diagnose heart disorders. Medical personnel can improve diagnostic efficiency by using automated ECG analysis techniques[2].

The heart is one of the most essential body parts to investigate. ECG is the most prevalent method for detecting and measuring the heart's electrical activity. ECG can assist physicians in diagnosing cardiac conditions such as arrhythmia, heart attack, and coronary artery disease. Traditional ECG analysis methods rely on trained specialists' manual interpretation of data, which can take time and differ from person to person. In recent years, deep learning has emerged as a possible method for diagnosing cardiac conditions using ECG signals. It has demonstrated excellent accuracy and rapidity[3].

12-lead Body-attached leads or nodes record an electrocardiogram (ECG). An electrocardiogram captures the heart's electrical activity. It transmits it to graph paper or an electronic vault in an electronic form that can be used for medical and security purposes by constructing a diverse dataset and presenting it to researchers for biometric systems[4]. Twelve-lead ECGs detect arrhythmia. Ten electrodes—six in the thorax and four in the extremities—measure electrical potential in these examinations. Early diagnosis is essential for treating arrhythmias[5].

1.2 Motivation

Nowadays, people are required to keep up with the high pace of life, in addition to irregular diet, lack of physical activity, etc., causing many heart problems and diseases.

To save time for medical assistance detection of cardiovascular problems, and contribute to the development of electronic health tools and early detection and prevention of cardiovascular diseases. 17.9 million People die from heart disease.

This was an incentive to build different systems aimed at detecting heart diseases. This gives great importance to research into heart health and the development of more advanced prevention tools. Therefore, it will contribute to improving cardiovascular diagnostic techniques, especially in the field of electrocardiography (ECG).

1.3 Problem Statement

It is a well-established fact that cardiovascular diseases are the leading cause of mortality globally, underscoring the critical need for early detection.

The objective of this study is to enhance the delivery of medical care by advancing the early detection of cardiac conditions. This goal is realized through the development of a comprehensive system with the capacity to accurately identify and diagnose a wide range of cardiovascular illnesses, which includes but is not limited to coronary artery disease (CAD), hypertension (HYP), myocardial infarction (MI), and supraventricular tachycardia (STTC). This system is designed to assist physicians in achieving precise and swift diagnoses.

1.4 Aim and Objective

The thesis aims to design a system that is easily able to determine whether the heart beating is healthy or abnormal based on the electrocardiogram by using deep learning techniques which have been used to support the specialists in diagnosing the four classes of most common cases of heart disease based on a global data set. To accomplish this aim, the following objective should be done:

- Preprocessing.
- Establish line-based behavior to CNN.
- Apply and load base dataset.
- Feature Extraction.
- Classification using deep learning.
- Design Anomaly detection.
- Evaluation.

1.5 Related work

Various studies on diagnosing heart diseases are based on the electrocardiogram. The following are the most important studies close to the proposed system within three time periods 2021-2023.

- **(Wang et al. 2020)[6]**, The primary objective was to develop an innovative method for myocardial infarction (MI) detection using electrocardiogram (ECG) data. To enhance the model's robustness and prevent overfitting, the dataset was expanded. First-layer representation incorporated Principal Component Analysis (PCA), statistical features, and entropy features. Subsequently, Random Forests (RF) were employed to extract second-layer features. The method's effectiveness was assessed through intra-patient and inter-patient schemes, resulting in robust outcomes. In the intra-patient scheme, the model achieved

89.71% accuracy, 89.7% sensitivity, 89.73% specificity, and an F1 value of 89.71%. In the inter-patient scheme, it maintained strong performance with 85.82% accuracy, 73.91% sensitivity, 87.73% specificity, and an F1 value of 83.9%. These results underscore the method's effectiveness in MI detection.

- **(S. Clement Virgeniya & E. Ramaraj.2021)[7]:** Proposed a system that employs a combination of a Repeated Gated Unit (Gated Recurrent Unit) and an Extreme Learning Machine (ELM) for deep learning, focusing on ECG signal analysis. This model utilizes the CIGRU-ELM framework, encompassing essential stages for preprocessing, data sampling, feature extraction, and classification. To address class imbalance issues within the neural network, the system integrates ADASYN (Adaptive Synthetic) for correction. The Gated Recurrent Units (GRUs) are responsible for extracting vector-related features, and the final stage involves the ELM model, which categorizes ECG test signals utilizing the PTB-XL dataset.
- **(F.Yang et al.2021)[8]:** a novel approach is introduced, presenting a weakly supervised pretraining method rooted in the Siamese neural network framework. This method harnesses original diagnostic information written by physicians to create valuable feature representations for ECG signals, subsequently enhancing the performance of ECG abnormality detection algorithms with reduced expert annotations. The experimental results underscore the efficacy of this approach; notably, ECG abnormality detection algorithms trained with ECG data outperform classical models trained with fully annotated data, implying substantial savings in annotation resources. Additionally, the adaptability of this technique is highlighted, as it can be readily extended to various other tasks, contingent on the design of a task-specific text similarity metric.

- **(S. Karthik, et al.2022)[5]:** A system for automating the detection of 1D biological ECG signals for heart disease diagnosis, referred to as Deep Learning Cardiovascular Electrocardiogram Diseases (DLECG-CVD), is proposed. This system encompasses preprocessing, feature extraction, hyperparameter tuning, and classification. Data preprocessing is the initial step in preparing ECG data for subsequent analysis. Deep Belief Networks (DBN) are employed to generate feature vectors, and their hyperparameters are optimized with the assistance of an Information System Security Officer (ISSO). Finally, eXtreme Gradient Boosting (XGBoost) is utilized for the classification of ECG signal tests. Simulations conducted with the DLECG-CVD models demonstrate enhanced diagnostic performance when applied to the PTB-XL benchmark dataset.
- **(J. Qiu et al.2022)[9]:** proposed system focuses on a new data augmentation method to improve heart disease detection robustness and accuracy in imbalanced ECG datasets. Optimal Transport balances ECG sickness and regular beats. Multi-Feature Transformer (MF-Transformer) categorization employs temporal and frequency data to diagnose heart issues. The 12-lead ECG can detect five cardiac disorders. Classification algorithms can predict five ECG types competitively, and our data augmentation technique enhances accuracy and resilience.
- **(Q.Geng et al., 2023) [1]:** In the existing literature, a novel multi-task deep neural network architecture is presented, comprising a shared low-level feature extraction module, namely the Squeeze-and-Excitation Residual Network (SE-ResNet), along with a task-specific classification module. Notably, this architecture incorporates the Contextual Transformer (CoT) block within the classification module to dynamically capture both local and global information within the

ECG feature sequence. The performance of this method has been assessed using publicly available datasets, specifically the CPSC2018 and PTB-XL datasets, yielding an impressive average F1 score of 0.827 on the CPSC2018 dataset and an average F1 score of 0.833 on the PTB-XL dataset. These results contribute to the growing body of research on deep neural networks in the context of ECG analysis.

- **(Xiao et al. 2023) [10]**, They investigated the clinical applicability of their initial model design by categorizing a large-scale ECG dataset into MI and non-MI groups, while also considering MI-confounding conditions. They executed two experiments to evaluate the impact of ECG duration and the inclusion of multimodal information within their model. They introduced a groundbreaking multimodal deep learning architecture for extracting features from ECG data and patient demographics. Their results revealed that the multimodal model outperformed the ECG-only model, achieving an average AUC of 92.1% and an accuracy of 87.4%. These findings exhibit promise for clinical applications, even in the face of challenging class definitions, underscoring the potential of their multimodal deep learning approach.

The accompanying Table (1.1) summarizes the work covered in the preceding section.

Table (1.1): Comparison of related work.

RF	Method	Dataset	Limitation	Result
2020 [6]	- Random Forests (RF). - Inter-patient scheme (IPS)	PTB MI ECG	The study may not cover all diagnostic features.	RF Acc.=89.71%, Sens.=89.71% Spec.=89.73%, F1=89.71% IPS Acc.=85.82%, Sens.=73.91% Spec.=87.73%, F1=83.9%
2021 [7]	-(Siamese neural network) -(Ordinary Differential Equations net) **ODENet**	PTB-XL	Doesn't specify the epochs used to get findings. Did not define how to divide the dataset into training and testing	CD Acc.= 0.9296, F1= 0.8594 MI Acc.= 0.8707, F1= 0.7485 HYP Acc.= 0.9221, F1= 0.8265 STTC Acc.= 0.8960, F1= 0.8040 NORM Acc.= 0.8516, F1= 0.9166
2021 [8]	(CIGRU-ELM) from GRU&ELM	PTB-XL	Only 2965 out of 21837 ECG signals were used. Feature selection was implicit in deep learning. Combining the normal class with others affected accuracy.	CD Acc.= 0.885, Sens.= 0.974 Spec.= 0.547, Prec.= 0.890 F1= 0.930 MI Acc.= 0.885, Sens.= 0.985 Spec.= 0.459, Prec.= 0.887 F1= 0.933 HYP Acc.= 0.957, Sens.= 0.999 Spec.=0.604, Prec.= 0.955 F1= 0.976 STTC Acc.= 0.864, Sens.= 0.967 Spec.= 0.508, Prec.=0.871 F1= 0.917 NORM Acc.= 0.774, Sens.= 0.715 Spec.= 0.823, Prec.= 0.774 F1= 0.743
2022 [5]	DLECG-CVD	PTB-XL	Only 2965 out of 21837 ECG signals were used. Feature selection was implicit in deep learning. Combining the normal class with others affected accuracy.	CD Acc.= 0.9022, Sens.=0.9851 Spec.=0.5907, Prec.= 0.9005 F1= 0.9409 MI Acc.= 0.8988, Sens.=0.9933 Spec.=0.4929, Prec.= 0.8938 F1= 0.9409 HYP Acc.= 0.9575, Sens.=0.9992 Spec.=0.6076, Prec.= 0.9553 F1= 0.9768 STTC Acc.= 0.8772, Sens.=0.9743 Spec.=0.5427, Prec.= 0.8801 F1= 0.9248

2022 [9]	-(MF-Transformer)	PTB-XL	Deals with ECG data imbalance and predicts cardiac illness but not all five groups. Data imbalance boosts NORM and CD accuracy, possibly impacting the other three heart disease categories.	Average Accuracy=75.82% F1-score= 0.757
2023 [1]	SE-ResNet	PTB-XL CPSC2018	- Achieve multitasking using only the co-hard parameter. Use ECGs from Planes IX and X as validation and test sets, validated by at least one cardiologist.	CD Acc.= 0.868, Prec.= 0.867 Rec.= 0.872, F1= 0.869 MI Acc.= 0.912, Prec.= 0.814 Rec.= 0.734, F1= 0.772 HYP Acc.= 0.883, Prec.= 0.852 Rec. = 0.819, F1= 0.835 STTC Acc.= 0.869, Prec.= 0.834 Rec.= 0.813, F1= 0.823 NORM Ac.= 0.905, Prec.= 0.877 Rec.= 0.676, F1= 0.863
2023 [10]	**CNN**	PTB-XL	Reliance on preset probability threshold for labeling impacts evaluation metrics. Four subclasses within non-MI conditions complicate false-positive analysis. SHAP values are used for interpretability, but complex feature interactions remain challenging to understand.	AUC=92.1% ACC=87.4%.

1.6 Layout of Thesis

This dissertation's research is organized into the following chapters. In addition to the first chapter, the thesis consists of four other chapters, which are organized as follows:

Chapter One: The first chapter (General Introduction), the other chapters in this thesis are follows as:

Chapter Two: This chapter describes general algorithms and approaches.

Chapter Three: This chapter presents the parts of the proposed system including algorithms and methods.

Chapter Four: Describes the outcomes of the proposed.

Chapter Five: This chapter presents the conclusions and suggestions for future work.

الخلاصة

التقدمات الأخيرة في مجال تكنولوجيا المعلومات والذكاء الاصطناعي أثرت في مجال الرعاية الصحية بشكل جذري وأدت إلى تحول معروف باسم "الرعاية الإلكترونية". هذه الثورة تستخدم التعلم الآلي، مثل الشبكات العصبية التكرارية المختلفة ((CNNs، في تشخيص الأمراض، ولا سيما في أمراض القلب. تمنح الرعاية الإلكترونية المهنيين في مجال الرعاية الصحية تشخيصًا دقيقًا وفوريًا، خاصة فيما يتعلق بأمراض القلب. يساعد التعلم الآلي في تحليل البيانات، والتعرف على الأنماط، وتقديم علاج دقيق، مما يعزز نتائج المرضى. هذا التكامل يشير إلى تحول نحو رعاية مريض محورية قائمة على البيانات، مما يعزز إمكانية الوصول إلى الرعاية الصحية وفعاليتها.

النظام المقترح لتشخيص حالات القلب، والمعتمد على القراءة الكهربائية للقلب ((ECGs وتقنيات التعلم العميق، يستفيد أساسًا من خوارزمية CNN لزيادة دقة التشخيص وكفاءته. يتألف النظام من ثلاث مراحل رئيسية: المعالجة المسبقة والتدريب والتصنيف/التنبؤ، حيث تلعب خوارزمية CNN دورًا حيويًا في بنية النظام. باستخدام مجموعة البيانات PTB-XL (PhysioNet/Computing in Cardiology Challenge 2020 Extra Large)، يمكن للنظام أن يقوم بالتنبؤ بالعينات الصحية والمصابة.

يدعم النظام التعلم العميق ويستفيد من أهم مجموعات البيانات العالمية (مجموعة البيانات (PTB-XL، والتي تمت موافقت عليها مسبقًا من قبل الباحثين. تم تصميم هذه المجموعة لتشخيص أو التنبؤ بأربع حالات مرضية هامة للغاية، وتحديدًا التغييرات في ST/T (STTC)، الإصابة العضلية ((MI، اضطرابات النظم ((HYP، واضطرابات وشذوذات الانتقال والتوصيل (.(CD

قدم النموذج التصنيفي نتائج استثنائية من حيث الدقة، حيث تراوحت القيم بين حوالي 94.64% و96.41% للفصول المختلفة للأمراض. كما أظهرت الدقة في الأداء الاستثنائي بنسب تجاوزت 94% بانتظام، مع تحقيق أعلى نسبة تصل إلى 97.90%. ذلك يُشير إلى دقة النموذج في التنبؤ بالحالات الإيجابية. بالإضافة إلى ذلك، تجاوزت القيمة في نسبة الاستدعاء الـ 96% بانتظام، ووصلت إلى 98.05% في حالات معينة، مما يسلط الضوء على قدرته على التعرف بشكل صحيح على الحالات الإيجابية. أما نسبة الدقة والاستدعاء (الحساسية) فقد أظهرت توازنًا رائعًا بين الدقة والاستدعاء، حيث تراوحت القيم بين 96.07% و98.83%. هذه النتائج تؤكد جماعيًا على أداء النموذج القوي في تصنيف وتحديد حالات الأمراض بدقة، مع دقة استثنائية ودقة واستدعاء ونسبة F1 ممتازة.