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Design of a TinyML-Based Predictive Heart Disease Screening Device

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Abstract - Cardiovascular disorders have become a global issue. There is a prevalence of heart failure and its impact on public health, particularly in regions with limited healthcare resources such as Africa. To combat this challenge, governments and healthcare institutions have initiated awareness campaigns and infrastructure improvements. Technological advancements, particularly in machine learning, offer promising solutions for early detection and prognosis. This study explores the application of Tiny Machine Learning (TinyML) in the context of heart disease, leveraging its potential for quantized models on resource-constrained devices. The research examines traditional diagnostic methodologies and highlights the application of TinyMLin predicting heart failure. The research contributes a unique perspective by deploying a Shallow Neural Network (SNN) model on an Arduino BLE 33 Sense for heart failure prediction, focusing on eight features. The resulting classification report demonstrates the model's accuracy of 82.61% and ROC_AUC of 92.15% for both absence and presence of heart disease. This paper serves as a foundation for future enhancements and applications in predictive healthcare technologies.

Keywords-Cardiovascular disorder, Tiny ML, Neural Network, Microcontroller

I. INTRODUCTION

Cardiovascular disorders, encompassing heart failure, pose a substantial worldwide public health issue. Being one of the primary contributors to global mortality rates, they impose a significant strain on healthcare systems and communities [1]. The prevalence of cardiovascular illnesses, particularly heart failure, is a matter of great concern in places such as Africa, where limited access to healthcare resources and inadequate disease management infrastructure provide substantial obstacles[2]. In the given setting, governmental bodies and healthcare institutions have undertaken significant measures to address the high incidence of cardiovascular illnesses through the implementation of public health awareness initiatives and enhancements in healthcare infrastructure. Heart illness cover a diverse range of illness, which include but are not limited to coronary artery disease, valve anomalies, and heart failure[3]. Heart failure is a chronic ailment distinguished by the heart's inadequate ability to efficiently circulate blood and oxygen to fulfill the physiological demands of the body[4]. The aforementioned problem presents itself as a potentially fatal ailment characterized by symptoms such as dyspnea, tiredness, and edema, resulting in a significant decline in the overall well-being of affected individuals. Regrettably, heart failure constitutes a significant proportion of premature mortality in Africa and several other geographical areas world wide [5].

There is a growing recognition among governments and health organizations regarding the imperative nature of tackling cardiac illnesses. To address the consequences of these circumstances, resources are being allocated towards augmenting public awareness, early identification, and intervention. These initiatives encompass the promotion of lifestyles that are conducive to heart health, the provision of training for healthcare professionals, and the facilitation of inexpensive access to drugs and therapies[6].

In recent years, technological advancements have played a pivotal role in the battle against heart diseases[7]. One of the most auspicious technical methodologies entails the utilization of machine learning for the early detection and prognosis of cardiac illnesses, including heart failure[8]. This methodology possesses the capacity to transform the healthcare domain, allowing proactive and individualized therapies.

II. LITERATURE REVIEW

The identification of cardiac disease in a clinical setting necessitates a thorough methodology that integrates an individual's medical history, physical assessment, and a range of diagnostic examinations. The assessment of patients' medical histories includes an evaluation of several criteria, such as their symptoms, lifestyle choices, family history of heart disease, previous medical illnesses, medicines, and risk factors, which comprise smoking, high blood pressure, diabetes, and high cholesterol.

Subsequently, a comprehensive physical examination is conducted, whereby healthcare professionals auscultate the patient's cardiac and pulmonary regions, assess blood pressure, and visually inspect for observable manifestations such as lower limb edema or cardiomegaly. Diagnostic tests are of significant importance in the medical field, and among them, the electrocardiogram (ECG) serves as a valuable tool for collecting and analyzing the electrical activity of the heart[9]. By doing so, it aids in the detection and characterization of irregular heart rhythms and abnormalities in the heart muscle. Echocardiograms provide comprehensive visual representations of the anatomical and physiological aspects of the heart, so enabling the identification of valve malfunctions, irregularities in the heart chambers, and the overall efficiency of cardiac pumping[10].

Stress tests are utilized to assess the cardiovascular system's reaction to physical exertion, hence assisting in the identification and evaluation of medical disorders such as coronary artery disease. Blood tests are utilized to assess several elements associated to the heart, such as levels of cholesterol, indicators of inflammation, and cardiac enzymes that indicate damage to the heart muscle. Various imaging modalities such as chest X-rays, magnetic resonance imaging (MRI), and computed tomography (CT) scans offer valuable insights into the dimensions, morphology, and potential pathological manifestations of the heart. In order to directly evaluate intracardiac pressure and detect abnormalities in blood circulation, medical professionals utilize techniques such as cardiac catheterization. If necessary, operations such as coronary angioplasty may be conducted. Holter monitors are utilized to monitor cardiac activity for a duration of either 24 or 48 hours, with the purpose of identifying any abnormal heart rhythms.

On the other hand, coronary angiography is a diagnostic procedure that allows for visualization of blockages or narrowing of arteries, which may be symptomatic of the presence of coronary artery disease. The choice of diagnostic tests is determined by the individual patient's unique circumstances, symptoms, and the clinical judgment of the healthcare practitioner. This process aims to conduct a thorough assessment in order to get an accurate diagnosis of cardiac disease and develop suitable strategies for treatment and management[11]

Tiny Machine Learning (TinyML) is a transformative technology that combines machine learning with embedded systems to deploy compact, low-power machine learning models on resource-constrained devices[12], [13]. In the healthcare sector, TinyML applications are making significant strides, particularly in the context of heart disease[14]. These applications include wearable heart rate monitors for continuous monitoring and arrhythmia detection, ECG analysis for real-time heart rhythm assessment, predictive risk assessment to identify high-risk individuals, telemedicine and remote monitoring for efficient patient care, and medication adherence systems[15], [16]. Additionally, TinyML plays a crucial role in predicting sudden cardiac events by analyzing data from wearable devices.

This section offers a comprehensive analysis of significant publications and research initiatives that highlight the utilization of Tiny ML in the detection of cardiovascular diseases.

Nagavelli U. et al.presented a method to help clinicians to diagnose heart problems at the early stage. Several machine learning models including Naïve Bayes, Support Vector Machine (SVM) with XG Boost. It first proposed Naïve Bayes, with a weighted approach in predicting heart disease. Further tests were done implementing an improved SVM based on the duality optimization scheme. Finally, they used Clinical Decision Support System (CDSS) which includes density based special clustering[8].

A study by Hussain L. et al. involved the ranking of multimodal features collected from people with congestive Heart Failure (CHF) and Normal Sinus Rhythm (SNR). The rated characteristics were classified into five groups, ranging from 1 to 5, using Empirical Receiver Operating Characteristics (EROC) values. Robust machine learning methodologies, including Decision Trees (DT), Naïve Bayes (NB), Radial Basis Function Support Vector Machine (SVM RBF), and Polynomial Support Vector Machine (SVM Polynomial)[17].

Alom Z. et al. in their research did a comparative study of detecting heart failure using six machine learning models which are Logistic Regression (LR), Naïve Bayes (NB), Random Forest (RF), Decision Tree (DT), Support Vector Machine (SVM), and K-Nearest neighbor (K-NN) to predict heart attack[18].

Bengherbia B et al. proposed a system which automatically detect and classify different cardiovascular diseases using a one dimensional convolutional Neural Network. The CNN model was implemented using MIT-BIH ECG database from Physionet where the accuracy and loss were 97% and 0.11% respectively[15].

The above literatures have demonstrated the use of various machine learning algorithms in prior studies for heart failure detection. Our research brings a unique perspective, emphasizing model training through Shallow Neural Network (SNN) deployed on an Arduino BLE 33 Sense. We focus on eight pivotal features: age, gender, resting blood pressure and maximum heart rate, Cholesterol, Fasting Blood Sugar, Resting ECG and Old Peak known for their significance in heart health assessment.

III.MATERIALS AND METHODS

In this section, the various materials and methods used in the dataset acquisition and preprocessing, training and testing, and deployment of trained model are highlighted as depicted in figure 1.

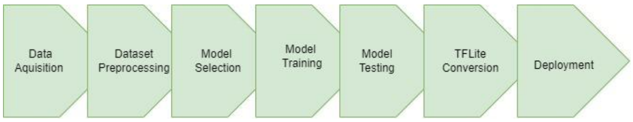

Figure 1: System design flowchart

1.System Software

Dataset Acquisition and Preprocessing

The dataset obtained in this study was obtained from Kaggle and is publicly availableat[19]. It comprised of 918 samples and 12 features including age, gender, resting blood pressure and maximum heart rate, Cholesterol, Fasting Blood Sugar, Resting ECG and Old Peak, Exercise Angina, Chest Pain Type and ST_Slope. The target variable, denoting the presence or absence of heart disease, is coded as 0 or 1.To gain insights into the dataset's characteristics, we examined the distribution of the target variable.Chart 1 presents the distribution of the target variable across the dataset. The graph is a bar chart illustrating the frequency of each category or class within the target variable.This dataset was created by combining different datasets already available independently but not combined before. In this dataset, 5 heart datasets are combined over 11 common features which makes it the largest heart disease dataset available so far for research purposes [19]. Eight out of the eleven features were selected as they are known in their significance in heart health assessment.

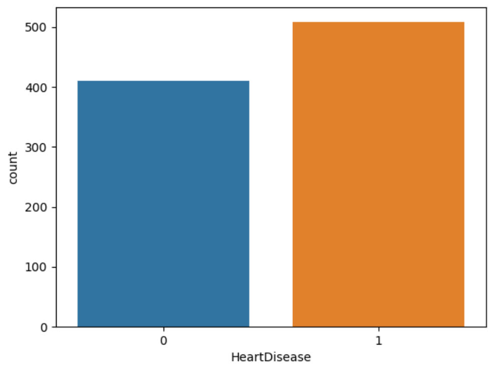

Chart 1: Distribution of the Target Variable.

In chart 2, we show a histogram of the distribution of the eight selected features across the dataset.

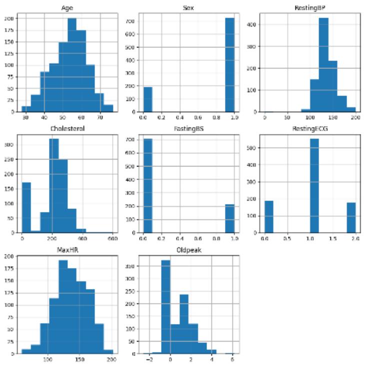

Chart 2: Distribution of the 8 selected features

Shallow Neural Network Model

We employed a Shallow Neural Network (SNN) model for training the heart disease prediction dataset. Neural Network a computational model inspired by the biological neural networks found in the human brain. These artificial neural networks consist of interconnected layers of neurons, with each neuron processing inputs, applying weights, and using an activation function to produce an output[20].

The network architecture depicted in figure 1 consists of three layers- an input layer, a hidden layer and an output layer, with ReLU activation function. The input layer has eightneuronsand the output layer, which is designed to predict heart failure.

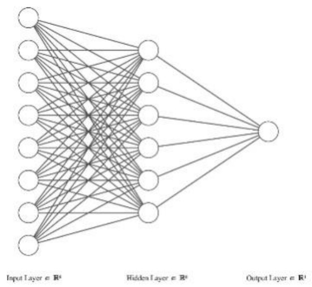

Figure 2: The Neural Network Architecture

Deployment

The model was converted and quantized with Tensorflow Lite into a form which can be loaded on a resource constrained microcontroller.The device for deployment is an Arduino Nano 33 BLE Sense (Cortex-M4F64 MHz, Arduino, Somerville, MA, USA), which is characterized by its compact size andsuitability for various applications. With a maximum available RAM of 256 kB and a ROM of 1024 kB, the device offers limited computational resources.

System Hardware

The system is implemented with four fundamental hardware components: a liquid crystal display (LCD) represented in figure 3, the Arduino BLE 33 Sense illustrated in figure 4, and additional components including a button (figure 5) and a potentiometer (figure 6).

Figure 3: LCD 20x4

Figure 4: Arduino BLE 33 Sense

Figure 5: Potentiometer

Figure 6: Button

The LCD serves as a visual interface, providing information to the user. The Arduino BLE 33 Senseserves as the core microcontroller, facilitating the integration and execution of the prediction and the potentiometer and the button functions as the input devices for inputting patient's data. The circuit design is illustrated in figure 7. The design comprises of ATMega 328 P, a 20x4 Alphanumeric LCD, a potentiometer and a button. This is to illustrate the circuit connections of the various components.

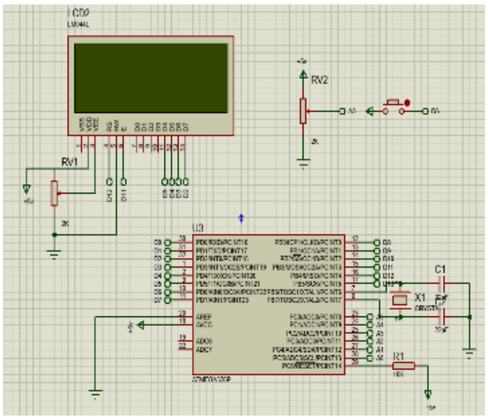

Figure 7: Schematic diagram of the device

IV. RESULTS AND DISCUSSIONS

In order to train and validate the SNN model, the dataset was split into 80% for training, 10% for cross validation and 10% for testing. The system achieved a significant accuracy and ROC_AUC score.

Table 1: Classification report.

	Precision	F1-Score	Recall	Support
0	0.88	0.81	0.84	53
1	0.77	0.85	0.80	39
Accuracy			0.83	92
Macro Average	0.82	0.83	0.82	92
Weighted Average	0.83	0.83	0.83	92

The presented classification report in table 1 details the performance metrics of the model. For class 0, which represents the absence of heart disease, the model achieved a precision of 88%, indicating its accuracy in predicting instances of class 0 out of all instances classified as such. The recall for class 0 was 81%, illustrating the model's ability to capture a substantial portion of actual instances of class 0. The harmonic mean of precision and recall, represented by the F1-Score, was 84%, providing a balanced evaluation for class 0. Similarly, for class 1, which represents the presence of heart disease, the model demonstrated a precision of 77%, capturing instances of class 1 with an 85% recall. The F1-Score for class 1 was 80%. The overall accuracy of the model was 83%, and the macro average, considering both classes, was 82%. The weighted average, accounting for class imbalances, was 83%.

V. CONCLUSION

In the presentstudy,a design of a predictive heart disease screening device based on a Neural Network model has been presented. The model exhibited robust performance, with high precision and recall values for both classes, 0 and 1, signifying its accuracy in correctly classifying instances. The balanced F1-Scores for both classes further underscore the model's ability to provide reliable predictions. Notably, the weighted average, accounting for class imbalances, yielded a favorable accuracy of 83%, reinforcing the model's effectiveness in handling varying class sizes. This paper underscores the potential of the proposed system for real-time heart disease screening, offering a foundation for future enhancements.

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