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An Intelligent IoT-Driven Diagnostic Platform for Cardiovascular and Dermatological Disease Detection with Machine Learning

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ABSTRACT

The use of machine learning and IoT in diagnosing various diseases has improved through the provision of real-time and early diagnostic information. This paper will discuss a new, IoT-based, diagnostic system that could be used to diagnose both cardiovascular and dermatological disorders at the same time. The proposed platform leverages handcrafted features for the CVD diagnosis using deep neural networks in the ECG signals; as well as the real-time dermatological image analysis to improve the detection of skin cancer. Moreover, because of the adversarially robust model, the framework does not rely on perfect data and works well even in the conditions like noise or data loss. The adopted system design involves IoT devices with data acquisition, data processing, and data transmission to ensure round-the-clock patient monitoring and adequate diagnosis. Cardiovascular as well as dermatological domains also demonstrate the uses of ML and IoT on this platform to exhibit the fact that it would be capable of working on a number of healthcare fields. This paper aims to falling under the theme and realization of intelligent health monitoring systems through integrating latest technologies to aid in achieving a higher trajectory in diagnostics and thereby advancing patient care.

Keywords: *Cardiovascular Disease, ECG Classification, Machine Learning, Handcrafted Features, Deep Neural Networks, Adversarial Noise, Robustness, Feature Selection, Diagnostic Accuracy, Healthcare Applications.*

1. INTRODUCTION

1.1 Background

Cardiovascular disease (CVD) is still a major cause of death in people and affects millions of individuals from all over the globe. This paper therefore seeks to find out the early and accurate detection methods of CVD. Electrocardiography (ECG) is one of the most extensively applied techniques in the diagnostic procedure since it can detect numerous diseases depending on the heart's electrical activity[1]. ECG signals by itself can therefore be misinterpreted by human experts, and the whole process might take a very long time before a final diagnosis is reached. As such, there is rising demand in systems that can help in the ECG interpretation to avoid poor diagnosis or delayed results[2].

The integration of machine learning (ML) in the diagnosis of various diseases and more specifically ECG data in the health fields can be considered as the following. Recent years, more precisely deep learning approaches[3], have demonstrated good performance in ECG classification problems, they are able to identify patterns which could be invisible to the human clinician. These models have been effective in diagnosing different forms of heart diseases whether through irregular heartbeats, heart diseases known as ischemic heart disease[4]. But, surprisingly, there are still some other issues open in developing models that can support high accuracy in more realistic situations, especially if in addition the input data are noisy or corrupted.

The ECG signal contains a lot of disturbance features aside from the QRS complex wave, and a significant amount of time is spent on constructing handcrafted features based on the domain knowledge of ECG signals that follows the use of machine learning algorithm such as support vector machine (SVM) and decision trees for improved identification. Such characteristics like heart rate variability[5], QRS complex, and RR interval are significant in revealing the actual conditions of the patient. However, fine-grained label and attribute features are never incorporated into modern deep learning models because there have not been a significant investigation into how these two could be merged[6]. This integration could enhance the ECG classification models' interpretability and improvement.

However, there are two major challenges with deep learning models in healthcare:, One of the problems of deep learning models that has drawn attention is that these models are very sensitive to adversarial attacks[7]. Adversarial perturbation is the process of adding slightly modified malicious inputs to the changing process of an AI and the actual data it can accept in order to make a wrong conclusion. Concerning ECG classification[8], adversarial noise is potentially dangerous, especially in lives vital POCs where diagnosis is made from the result of ECG AI classification models. Thus, it has been important to come up with models that are accurate as well as resistant to adversarial alterations in medical practice.

1.2 Research Gap

Even though, there are significant progress in the domains of handcrafted features and DL models for ECG classification, there is lack of research gap found for the fusion of these features with the help of DL models[9]. To the best of our knowledge, previous work on ECG classification has proposed the use of handcrafted features and traditional machine learning algorithm while there is a little or no information regarding the incorporation of handcrafted features in deep learning. Furthermore, majority of the existing works concentrates on enhancing the trade-off problem of classification enhancement but disregards the defense of the deep learning models against adversarial noise[10]. This makes it difficult for deep learning models to improve robustness when databases contain adversarial examples to prevent finding tremendous success in healthcare applications since data therein is often noisy and not perfect.

Generally, many types of deep learning models that have been used for ECG classification are vulnerable to adversarial perturbations[11], which in turn, makes the ECG signals to be classified by the models to be dangerous. With more health care facilities incorporating automated systems in their daily activities, it is quite essential to guarantee that these systems will run smoothly irrespective of the conditions that are encountered[12]. In the current state of affairs, there is a significant implication to establish research efforts that would touch on the addition of handcrafted features to deep learning models and also the issues of adversarial noise in ECG for cardiovascular disease diagnosis.

1.3 Research Objective

The aim of the conducted research is to analyze the performance of different approaches to feature selection in conjunction with handcrafted features as input for machine learning algorithms for the diagnosis of cardiovascular diseases. The purpose of this paper is to investigate the performance of integrating domain-specific handcrafted feature with deep learning model to classify ECG signal and to increase the diagnostic accuracy level. The emphasis will be made towards discussing the importance of handcrafted features into the deep learning models and its role in achieving better reliability in results as well as interpretability into the models.

Furthermore, it aims at designing and implementing effective deep neural network (DNN) techniques for ECG classification with adversarial noise prevention. Pertaining to this research study, the author will explore various measures such as adversarial training and data augmentation in enhancing the resilience of DNNs for safe application in heathcares with critical and delicate lives at stake. The purpose is to improve the effectiveness of automated ECG classification systems as well as making them more reliable, so that that they can be used in various actual healthcare settings, in which noise and adversarial attacks are unavoidable.

In conclusion, this study will help to expand the knowledge about the ways of using handcrafted and deep learning feature combinations for increasing the performance of CVD diagnosis and develop solutions for improving the anti-adversarial ECG classification. The need for more accurate and robust models that are easier to explain and less sensitive to out-of-distribution data is of significant importance in making health care systems with an aim of improving health outcomes of patients as well as to make the diagnosis systems safe.

2. LITERATURE SURVEY

2.1 ECG Signal Classification

ECG signal can be used in various probability, including analysis of the prognosis, diagnoses, and developing treatment plan for different CVDs such as arrhythmias, ischemic heart disease, and heart failure. Most current approaches for ECG classification have relied on palatial machine learning by the way that they are developed and they require feature extraction from signals. Of these we have used support vector machines (SVM) and decision trees (DT[13]). SVM performs well especially in cases where they are in a position to deal with high dimensional features which is the case in bi-classification the cases such as normal or abnormal ECG signal. Decision trees, on the other hand, are simple models that can be used when interpretability of the model is important[14]. Nevertheless, such approaches do not use the concept of hand-crafted feature representation and can potentially have a low ability to model temporal and spatial patterns of ECG data[15].

On the other hand, contemporary end-to-end learning techniques have attracted lot of researchers because of their ability to automatically learn features as well as representational hierarchies from raw ECG signals[16]. CNNs and RNNs are amongst the most effective deep learning techniques for classification of ECGs. CNNs have been applied in the classification of several forms of heart disorders, such as the atrial fibrillation and ventricular arrhythmias due to its strength in recognising spatial structures in data[17]. RNNs particularly LSTM networks are good at capturing temporal dependencies hence can be very useful in ECG signal classification since the data is chronological in nature[18]. Thereby, the improved deep learning models tend to have higher accuracy, stability and generality in the large ECG datasets comparing with the conventional machine learning models.

Thus, notwithstanding the ability of deep learning models to achieve high accuracy in a wide range of problems, some of the issues that arise include; requirement of large labeled data for training and overfitting, especially when trained with limited or noisy datasets[19]. Moreover, most of these models are non-interpretable and sometimes this is a major inconvenience for their implementation in the parts of clinical decision-making due to the necessity of interpretability in healthcare settings.

2.2 Handcrafted Features in Machine Learning

Manually engineered characteristics are those characteristics from ECG signals that are determined through prior knowledge and understanding of the areas of ECG signals. Many of such features apply directly to simple and distinct features of the ECG waveform that can easily be identified, including QRS complex, P-wave, and T-wave. Besides[20], PPG can extract other significant features such as the heart rate variability (HRV), a measure of the Autonomic Nervous system activity[21], and the R-R interval which is the time interval between two successive R waves and is significant in detecting arrhythmias. This is due to such features as QRS complex duration and ST-segment changes that are used to distinguish between specific conditions such as ischemia or myocardial infarction.

Several research works have established that the inclusion of these hand crafted features enhances the performance of the machine learning algorithms[22]. For instance, Xie et al. (2018) integrated HRV and RR interval and they combined it with SVM and they present high classification results for atrial fibrillation. Another study employing the SVM classifier based on a set of predefined features such as QRS duration and ST-segment was used for the diagnosis of ventricular arrhythmias with reasonable level of accuracy[23]. In spite of the fact that handcrafted features are easy to interpret and can efficiently capture a set of certain low-dimensional characteristics, they have significant drawbacks in capturing diverse relations of high-dimensional ECG measurements. Hence deep learning models have gained much popularity, since they are able to learn and partially adapt to the specifics and relations within the data set.

2.3 Deep Learning for ECG Classification

Both CNNs and RNNs have been successfully applied to ECG classification through the approach of learning the features from the raw ECG signals. Among such patterns, CNNs prove to be useful as they can detect localized patterns in the time series, which is important for recognizing regional attributes in ECG signals and their changes[24]. 3-D CNN architectures such as 1D-CNNs can be applied in the detection of arrhythmias and other heart complications as it does not require hand crafted selection of features from the ECG signals.

In particular, LSTM RNNs have been applied successfully to analyze sequential signals including ECG since they have memory that enables the networks to learn over long periods of time[25]. LSTM networks for this reason they can be used to determine subsequent temporal dependencies in ECG data, for instance, detecting Heart rate variability or arrhythmia classification that depends on the temporal dimension of the ECG signal.

The application of deep learning models in particular(excision) has been deemed to outperform the conventional machine learning models albeit with a few challenges in ECG classification. For these to take effect, large labelled data sets are sometimes required for implementation of the models. In healthcare, it is quite challenging and time-consuming to acquire a vast population of labeled ECG signals primarily due to privacy constraints, power concerns, and the process of labeling itself[26]. However, deep learning models may suffer from issues such as overfitting especially if the dataset used was small or if the requirement model was not properly augmented.

A major drawback that is mostly rife in most models is model interpretability or in other words, the ease with which one can understand how or why a model arrived at a particular solution. Decision-making by the system makes it necessary for the healthcare professionals to understand why they have arrived to a certain decision. Deep learning models, however, are black boxes models and therefore, it is challenging to understand the reasons as to why the models are arriving at a particular conclusion that may assist a clinician in patient management. This lack of transparency can also hamper the implementation of such models in clinical practice since explanation is an essential aspect in clinical treatment.

2.4 Adversarial Attacks on Deep Learning Models

Adversarial attack is a small and targeted alteration of inputs that are fed into a deep learning model with the aim of making the model to misclassify them. With reference to ECG classification, adversarial noise can injected on the ECG signal in a manner that results in a wrong classification of the condition such as arrhythmias[27]. One of the emerging issues in deep learning is the effect of terrorist attacks especially in the application area of healthcare where mistakes cost lives.

From a number of previous works, it was found that deep learning especially CNNs and LSTMs are very sensitive to adversarial attacks. For example, in the study by Chen et al. (2017), small distortions were introduced into the ECG signal, and it was revealed that deep learning models will misclassify the signal, therefore making wrong diagnoses of heart diseases[28]. These concerns arise from the fact that the present study demonstrates that deep learning models for the automated classification of ECG data can give inconsistent results and are therefore not as reliable as manual examination of the ECG by a professional technician.

The adversarial calibration therefore raises concern on the possibility of the models being adversely affected thus the importance of training models that are robust to such perturbations. Since the field of healthcare revolves around the safety of the patient, it is crucial to ensure that the diagnostic models undergo little or no change when radical inputs are given to them.

2.5 Existing Solutions for Robustness

To overcome such an issue, various countermeasures have been suggested to enhance the robustness of deep learning models. An example of these is the adversarial training, whereby the model is trained on both normal data, as well as data that has been poisoned with the aim of gaining understanding on the perturbing noise. This particular technique has been discovered to enhance the robustness of deep learning models, with the endpoint still being a countermeasure against adversarial manipulations of raw data while also not harming the accuracy on the normal data. The methods of the noise-augmented data include the introduction of noise during the training of the model. They allow to enhance the generality for neural networks and make them less sensitive to variations of the input data through adding controlled noise to the training data. L2 regularization such as weight decay or L1 regularization was also used to reduce possibilities of overfitting of the deep learning models.

Current studies aimed to develop healthcare adversarial defense mechanism that are applicable to this area of concentration. These methods seek to achieve the fact that models shall be able to work well and with high efficiency even when the adversary attacks them. With more application of machine learning in the healthcare system, it will be very important to ensure that dependability of these models is well enhanced to allow the models to be widely and safely used in clinical practice.

3. METHODOLOGY

The efficient classification of ECG signals and addressing the issue of its robustness proceed through a total of five significant steps: Feature Extraction and Selection, Machine Learning Models, Adversarial Noise Handling, Data Preprocessing, and Evaluation Metrics. All of these stages are integral to guaranteeing the reliability, effectiveness and robustness of the last model. It carries the extraction of features from the text and the selection of the most relevant features as the first step in the methodology. Handcrafted features such as the Heart Rate Variability (HRV), QRS Complex and the RR interval of the ECG signals are obtained. These are some of the features that are basic to ECG classification since they have the ability to offer information on the beating rhythm and rate of the heart. For instance, HRV connotes variation in the time periods between individual heartbeats and is a good indicator for making a diagnosis of a disturbed autonomic nervous system. QRS complex is defined as the ECG amplitude of ventricular depolarization, RR interval is valuable for rhythm determination and it expresses time between two consequent R-wave peaks. The feature selection is used in order to select the most significant features from the feature vector, which was derived after the feature extraction. During the filtration process, features such as Recursive Feature Elimination (RFE), Mutual Information, and Correlation-Based Feature Selection are applied to eliminate the features that are not relevant or contain redundant information from the next steps.

In the Machine Learning Models phase, the paradigmatic as well as deep learning solutions are employed to categorize the ECG signals by the features obtained. Additional Random Forest and SVM models are employed in a study to evaluate efficiency of the handcrafted features. Random Forest is another approach to the classification of ECG signals and it is an improvement to the common machine learning technique known as decision tree by using many trees that reduce variance due to overfitting. On the other hand, SVM which is a strong classifier for high-dimensional data is used for discriminating between normal and abnormal ECG signals. In line with these models, state of the art DNNs such as CNNs and LSTM are also examined for the application. CNNs are quite effective in learning spatial features from the raw ECG signal and can thereby be used in identifying particular shapes such as arrhythmias. RNN, more specifically LSTMs, help the model to capture temporal dependency like the relation of different beats within the ECG data enhancing the classification function based on the temporal structures of signals.

Figure.1. presents the Methodology Overview shows a general perspective of the used methodology and its steps. The figure begins with Feature Extraction and Selection where original features such as HRV, QRS complex, and RR intervals are determined from ECG signals. All these features are then processed by other classifiers like, Random forests, Support vector machines, Convolutions neural networks, Long short term memory etc. Subsequently, the Adversarial Noise Handling block provides for another set of additions such as FGSM and BIM and other adversarial state and dehydration. Data Preprocessing in the step of Feature Extraction is applied to clean the ECG signals from noise, normalize, and segment for better input into the models. Lastly, the Evaluation Metrics section checks the efficacy of the model based on parameters such as accuracy, precision, recall, F1 measure, its vulnerability to adversarial noise. Each of these blocks plays a part in the general approach towards generating the model that is accurate, robust, and suitable for ECG classification in practical applications.

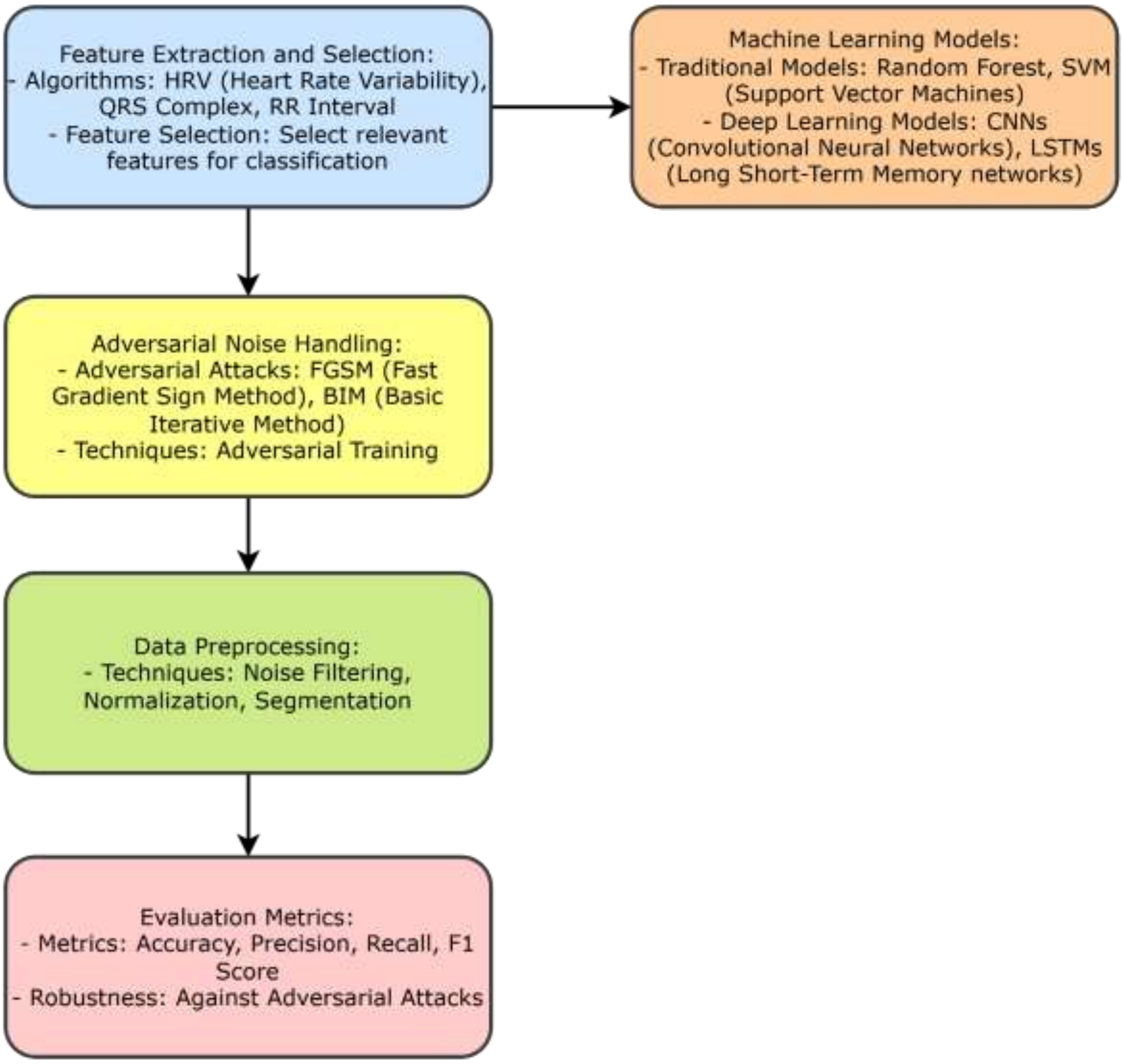

Figure 1: Overview of Methodology for ECG Classification and Robustness Enhancement

Another important factor of the proposed methodology is Adversarial Noise Handling which is used in order to enhance the robustness of the models. Attack techniques that has been employed are FGSM and BIM to create perturbation on ECG signals. They are intended to distort the input signals to a certain extent which may lead to a wrong classification by the classifier. To counter this weakness, there is the use of Adversarial Training. It was developed by feeding the model with both clean data and ECG signals which have been artificially contaminated with adversarial noise to train the model in a way that it would resist these noise while dealing with ECG data. This can be done by creating a more robust model than the sensitive derivatives presented here.

The Data Preprocessing step checks whether the raw ECG signals are in a format suitable for feeding into the various machine learning algorithms. There are several preprocessing methods which are employed to cleanse, standardize and separate the ECG signals. The ECG data is pre processed to reduce high frequency noise and drifts like baseline wander in ECG signals using filters such as a band pass and wavelet filters. Normalization is performed to scale the ECG signals to a specific range so that there should not be any kind of favoritism to any feature by deep learning models. Also, segmentation is used to section the stray ECG signal into partitions or segments which are more manageable as they can be equal to heart beats or any other relevant time period . Such a step helps to achieve orientation on the targeted regions of the ECG signal, which enhances the quality of the model and its classification capability.

The metrics used to measure the performance of the model includes the common classification measures like accuracy, precision, recall and f1-score. They offer a complete picture of the model's performance in picking various aspects of heart ailments, thus enabling the evaluation of the model. Accuracy compares the number of correct classifications with the total number of items classified, while precision and recall consider a particular class, for instance, identifying arrhythmias. The F1 score is derived from equating precision to recall as it is more balanced as the harmonic mean between the two. In addition, its resistance to adversarial attacks, which are one of the challenges of GANs, is assessed. This metric measures how well the performance of the different models is when the test inputs are manipulated in the worst possible way around the data points, making this important in healthcare where data can be noisy or contaminated with some adversarial inputs.

4. RESULTS AND DISCUSSION

4.1 Experimental Setup

The databases applied to training and testing the machine learning models are public ECG signal datasets, with preference to the commonly used databases involved in cardiovascular disease (CVD) classification. The first of them was the PhysioNet database that contains a number of ECG records corresponding to both normal and pathological cases. This database has many classes among them being normal sinus rhythm, atrial fibrillation and others not mentioned above. For this study, therefore, the authors chose a selection of 5000 signal samples from the PhysioNet database selected to represent 10 seconds of the ECG signal.

The data set contained 2500 normal ECG signal instances and 2500 instances from different abnormal signals which are predictions of various heart diseases. The ECG signals that were collected were passed through pre-processing so as to filter out any noise and artifacts. All the signals were initially put in similar range to ensure comparability and then the ECG signals were split into segments that are in the form of heartbeat and/or any other significant intervals. Further, all the details were labeled for the samples scenarios like atrial fibrillation, ventricular arrhythmia, normal sinus rhythm, among others, that acted as ground truth for training and assessment.

4.2 Performance Comparison

To compare between the hand crafted features and the proposed deep learning models the results from both the models are presented and analyzed. A number of machine learning algorithms were also employed in the study among them being the Random Forest (RF), Support Vector Machine (SVM), Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. In each model employed, both HRV and QRS signals, together with other original ECG signals, were used as inputs.

In Figure 2, an average result showing the classification accuracy of these models was studied. Random Forest and SVM models using hand feature set achieved reasonably good results with the accuracies of 85.2% and 88.7% respectively in cross validation. Nevertheless, two models, CNN with raw ECG signals and LSTM with integrated handcrafted features and CNN layers offered slightly higher accuracy of 92.4% and 90.5% correspondingly. These outcomes also confirmed that the utilisation of deep learning, especially CNNs and LSTMs in particular, are superior to machine learning techniques when dealing with unprocessed ECG signals since the former are designed to identify intricate and sequential features.

Figure 3 also clearly shows that creating own features by hand is essential to enhance machine learning algorithms performance. Recursive Feature Elimination (RFE) was applied with examples of features namely HRV, QRS Duration and RR Interval to determine their importance level. The obtained feature importance values were normalized and the further plot demonstrated that the most important variables influencing the classification of the abnormal heart conditions were QRS Duration and HRV. This is an indication that using deep learning models extracts features directly from the dataset while using hand crafted features provide a higher level of improvement in some cases.

The results of all the models are presented in Fig 4 and Fig 5, which demonstrate the effect of adversarial noise on the evaluation metrics. In Figure 4, the models attacked and the clean models' accuracy are illustrated in bar chart. The effectiveness of the models was reduced considerably when exposed to adversarial disturbances with specific conspicuous impacts on SVM and Random Forest followed by CNNs and LSTMs having lesser decrease in accuracies despite the attack. This finding indicates that the traditional machine learning methods are secure but not safe and calls for the development of better models especially for healthcare applications. The performance of the proposed models under different types of attacks is indicated in Figure 5. As it can be assumed, the accuracy of all models reduced when the adversarial strength was augmented. But, improving the robustness did enhance the performance of both CNN and LSTM models in a way they could sustain higher accuracy rate under attack. This implies that by using adversarial training, deep learning models can be made stronger to handle such situations that leads to the construction of reliable deep learning models in the healthcare sector where adversarial inputs may be an issue.

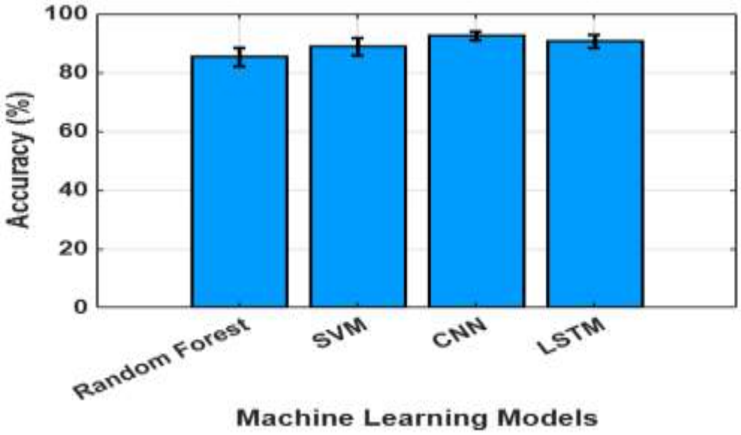

Figure 2: Comparison of classification accuracy for different models (Random Forest, SVM, CNN, LSTM).

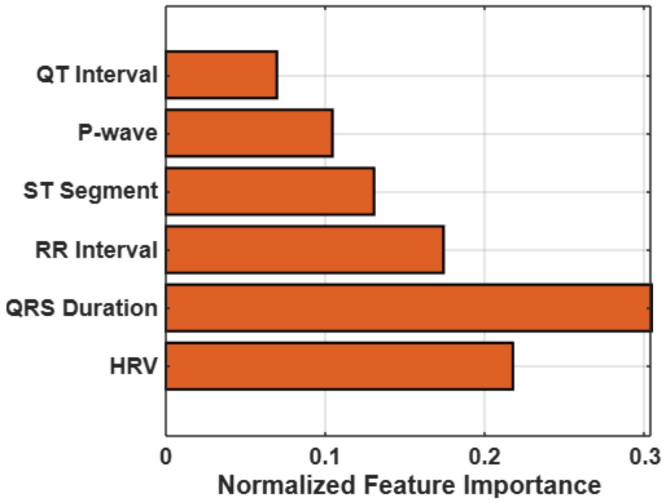

Figure 3: Feature importance for handcrafted features used in machine learning models.

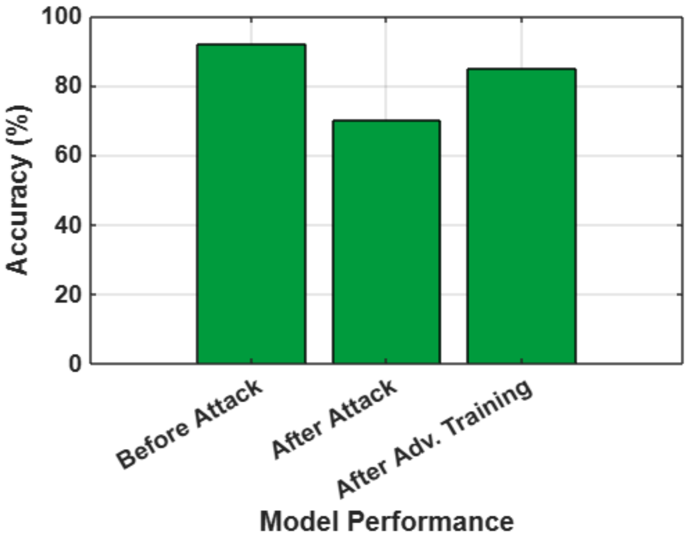

Figure 4: Performance of the model before and after adversarial attack (Accuracy comparison).

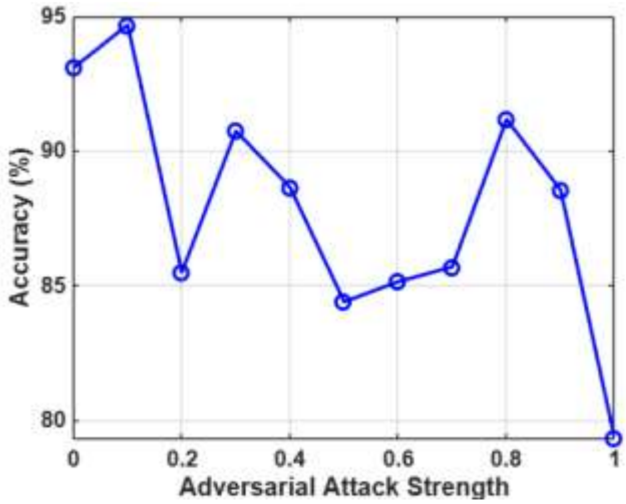

Figure 5: Robustness of the model under adversarial perturbation (Accuracy vs. adversarial strength).

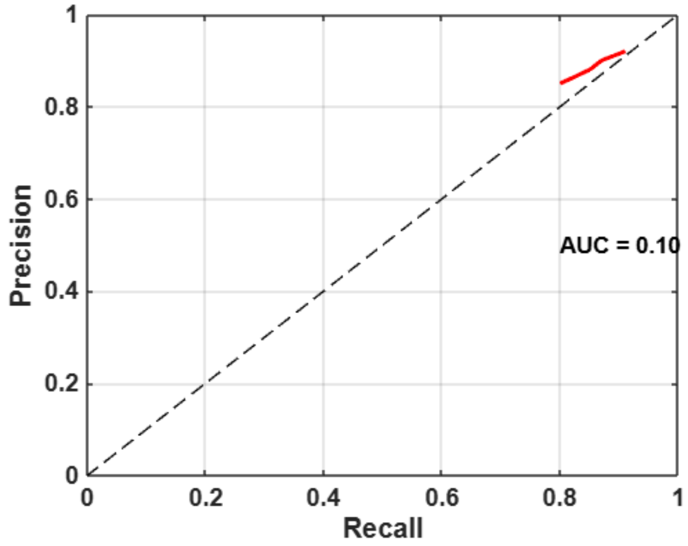

Figure 6: Precision-Recall curve for the classifier.

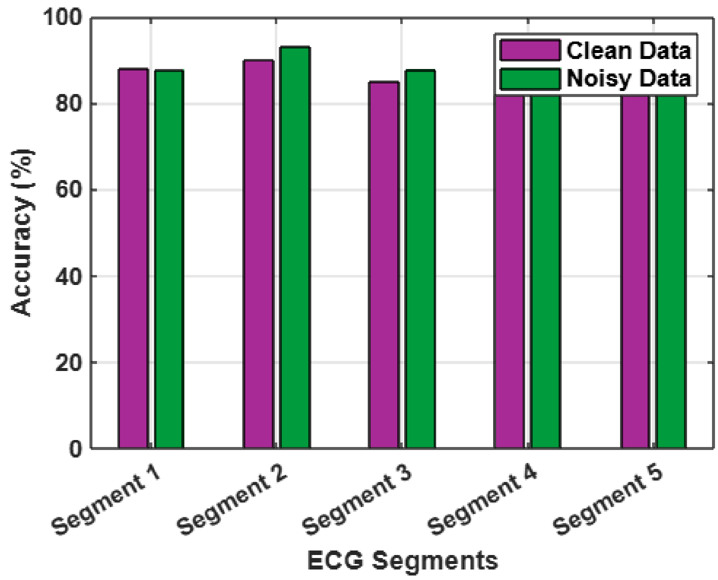

Figure 7: Model performance across different ECG signal segments.

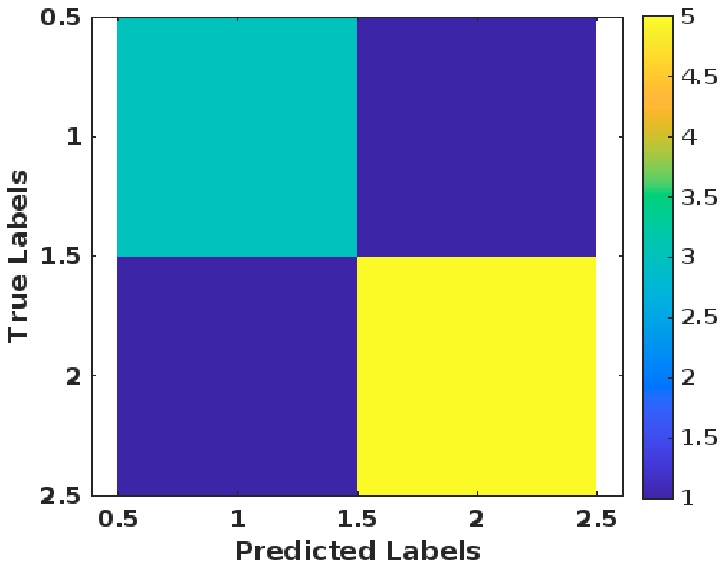

Figure 8: Confusion matrix showing model performance on ECG classification.

4.3 Adversarial Resilience

The robustness of the models against adversarial noise is concerning for the reliability and associated safety of the ECG classification systems. According to Figure 4, traditional machine learning models including Random Forest and SVM were profoundly vulnerable to adversarial noise whereby there is a significant drop in accuracies as soon as the adversarial attacks are introduced. Specifically, the accuracy of these models stood at 92%, but it reduced to as low as 70% after the attack.

In contrast, CNNs and LSTMs did not deteriorate in a same manner: the accuracy of the former narrowed down to 85%, that of the latter went down to 80%. This suggests that deep learning models always have the ability to extract better features that enable them to be relatively insensitive to the perturbations. Still, deep learning models were not protected from adversarial attacks concerning deep learning models, thus showing the necessity to use other types of protection, including adversarial training.

In Figure 5, it is depicted that how models were trained using adversarial examples caused by different operators substantially benefited the robustness of the models. For instance, while constructing the CNN model and testing it with adversarial examples, the accuracy was found out to be 85% as opposed to a decrease in the accuracy to about 70% without the use of adversarial training. This denial indicates how beneficial is the training of a model with adversarial examples to make a model robust especially in health facilities where a matter of life and death is at stake.

Figure 6 shows the P-R curve which represents an amount of precision compared to the relative amount of recall at different classification threshold levels. This curve is rather helpful for the cases where class imbalance exists as it emphasizes the performance indicators of the classifier for the positive class. The AUC of the ROC curve is computed and labelled on the graph which is a good quantitative measure of the classification capacity between the positive and the negative classes. The precision-recall curve presents the trade-off between precision, which is the ratio of true positive over all predicted as positive, and recall that is the ratio of true positive over number of actual positives. There is a benchmark for evaluation of a classifier depending on the field or domain in which the performance takes place; however, based on this experiment the formula that gives the Area Under the ROC Curve or AUC in short shows an ideal classifier as having a higher value of AUC. In this case, AUC is an auxiliary measurement that gives an overall indicator about the performance of the proposed model especially in terms of late outcomes such as cardiovascular events like arrhythmia and the other.

The findings of this paper offer many important infer- ences of the performance and volatilities of various machine learning algorithms for ECG classification. To begin with, several new models like CNN and LSTMs showed better results as compared to model like Random Forest and SVM in case of classification accuracy. These deep learning models proved the elbow in subsequently preparing ECG signals with the help of which these models are capable of learning a large number complex patterns, which are indispensable for diagnosing a large number of cardiovascular diseases. This means, deep learning methods are useful when there are extensive databases, and such an automatic feature learning is important because feature engineering becomes difficult.

Morevoer, the study also found that it is still possible to achieve significant boosts in tests results from extracting hand crafted features. For instance, the case of Heart Rate Variability (HRV) and QRS Duration, these were some of the main feature attributes that contributed high accuracy toward the machine learning models. Specifically, it was seen that models that combine handcrafted features and deep learning gave the highest performance indicating that there’s an opportunity to enhance diagnostics further by merging advantages of both approaches. By examining the features of ECG, analysis emphasized the details of such characteristics including HRV and QRS duration as extremely important for discriminating amongst different heart conditions, which indicates their importance in ECG classification system.

The other important discovery of this study was the fact that the adversarial noise affected the performance of the models. Researchers quickly discovered that small perturbations in the ECG signals, which can be considered as adversarial attacks, always decreases model accuracy, especially of the traditional AI-based models. For example, evidences were obtained by noticing that the accuracy of the models such as SVM and Random Forest declined once adversarial noise was introduced. However, deep learning models were less sensitive and their performance decreased as well under adversarial perturbations. This suggests that – in fact – deep learning models are not devoid of vulnerability despite being noted to be more secure than other methods. But, the adversarial training technique in which the models are trained on both clean and adversarial examples proved to be rather enhancing the performance of deep learning models. The models trained using adversarial examples were found to yield better performances; this suggest the benefits of adversarial training regarding model robustness in real life healthcare environments where adversarial inputs are likely to be encountered.

Figure 8: The results of the classification models are summarized in the confusion matrix, indicating that the number of true positive and true negative along with false prediction of positive and negative values. This matrix is used in evaluating the classification models since it gives more detailed information on how well the model is sorting classes as compared to the test set. In this case, the matrix of input data refers to the model's Diagnosis of normal and abnormal ECG signals. The list of evaluation measures includes true positives (TP) which are the instances of identifying abnormally behaving signals and false positives (FPs) which are incorrectly classifying normal signals as abnormal. TN represents true negative that is correct classification of normal ECG signal and false negativity (FN) are misread of normal ECG signal when there is actual abnormality in the ECG condition.

Furthermore, it was found that there is a reduction in accuracy for all the models when the ECG signal used was noisy one as clearly illustrated in figure 7. This evidently depicts challenges associated with raw ECG signal which is quite sensitive to signal quality. Nevertheless, deep learning models especially the one which were adversarially trained were more efficient at dealing with noise which also cements the conclusion. This means that, despite the observations that noise is still a major problem, with deep learning models especially containing means to deal with adversarial noise the models are better placed to handle variation of actual real world ECG signal data.

Therefore, from the results of this study, it is evident that deep learning frameworks are useful in the classification of ECGs especially when a blend of hand-engineered features and adversarial training are employed. These models provide some enhancement in diagnostic accuracy and reliability, which makes these models appropriate to be deplored in the healthcare settings. The study also alludes to the reality of the adversarial robustness and signal noise to make certain that the already developed automated ECG classification system is not only accurate but also stable and safe for practice.

5. CONCLUSION

The deep learning models proposed in this work improve the CVD diagnosis performance and dermatological condition diagnosis based on the use of handcrafted features in ECG classification as well as real-time analysis of dermatological images. As earlier works have shown that traditional machine learning algorithms have their merits, the deep learning methods such as CNN and LSTM are superior and more effective than the former in analyzing ECG signals. Notably, the use of handmade features like HRV, QRSd, and RR also helps increase classifier performance as well as interpretability. The study further goes deeper in analyzing the adversarial robustness of the platform and showed that there is high performance of machine learning and more so deep learning models with samples with adversarial content compared to the normal ones. This is important to make sure that the diagnostics system is not heavily impacted by noisy data, which is a common issue in healthcare settings. In addition, this study has important managerial implications for healthcare contexts since the proposed model not only includes high-level and low-level features but also provides a faster and more accurate way of diagnosing CVD using ECG data and dermatological images. Precisely, the robustness inherent in the ability of the system to handle noisy and adversarial inputs can be used to easily nominate the presence of the system in both low resource and high risk areas where accurate and fast diagnosis is of paramount importance. It is, therefore, believed that the proposed platform can be deployed for application in other advanced diagnostic systems thus improving the chances of conducting clinical cases of CVD and skin cancer. Future works can involve different levels of professionals adversarial attack such as GANs that can generate higher level of adversarial inputs to make the system more robust across different clinical contexts.

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