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Research Paper

A Computationally Efficient Hybrid Architecture for Accurate Myocardial Infarction Detection and Localization in ECG Data

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Abstract—Myocardial A cardiac event, or myocardial infarction (MI), happens when the blood stream to a part of the heart tissue is blocked. In a lot of cases, MI shows up with mild or unusual symptoms like tiredness, indigestion, or it might not show any symptoms at all until a lot of damage has been done. In extreme cases, it can cause abrupt hemodynamic collapse and even death. Most cases of MI have a connection to initial coronary artery disease (CAD), which is still one of the top causes of death in the US. Early detection and accurate localization of myocardial infarction are essential for averting additional cardiac complications and enhancing patient outcomes.

Current methods have created lightweight and effective machine learning-based systems their use features from single-lead ECG signals to automatically find different types of MI. An autonomous encoder and decoder network is used to learn representations on a that store the most important features of the cardiac rhythm signal in order to improve feature quality. Then, a mix of algorithms used for machine learning, such as Random Forest as well as XGBoost, is used to make the classification more accurate. These systems have done very well, with a reported accuracy of 96.75%.

To improve detection performance even more, the proposed framework adds a model that makes very expressive along with overfitted representations for ECG data. This model uses a DNN, or deep neural network, that was purposely trained in an overtime mode so that it can pick up even the smallest changes on the PTB-XL heart attack study data. This method greatly improves predictive performance by learning complex and relationships that are not linear in the data. When tested, the proposed model gets 99.90% accuracy on test data and almost perfect scores on other important performance metrics. This shows that it has the potential to be very reliable for MI finding and localization.

Keywords: myocardial infarction, MI notice, single-lead ECG features, autonomous encoder-decoder, randomly generated forest, XGBoost, PTB-XL dataset, overfitted representations, DNN.

I. INTRODUCTION

In the last few years, there have been big improvements in the areas of diagnosis and medical care. Even with these changes, heart disease is still one of the top causes of death around the world. The World Health Organization, or WHO, says that about 16.9 thousand individuals die each year from heart and blood vessel diseases. Chronic ischemic coronary heart disease (IHD) is the main cause of death. More than 8.9 million of these people have myocardial infarction (MI), which is more commonly known as heart failure. Cardiovascular

disease, angina pectoris, along with arrhythmia are common clinical signs of acute MI that can have serious effects on the people who have them. So, the prompt identification of MI is very important to avoid serious problems and make things better for patients.

Myocardial infarction develops in multiple stages, commencing with ischemia of the which results from a disruption in the normal supply of blood to the heart's chambers. If this ischemic condition is not treated, it can completely block blood flow, which can damage tissue and cause the heart to stop working. Cardiovascular diseases (CVDs) have a close connection to myocardial infarction (MI) and present considerable risks, especially for individuals with pre-existing cardiovascular diseases. Epidemiological studies show that the number of by appearance unrecognized MI cases rises with age, which shows how important it is to get a diagnosis quickly. Finding ischemic events early could save lives and let patients get the right care before damage that can't be fixed happens.

Random Forest when XGBoost are two examples of typical algorithms for machine learning that have been used to find MI, but they don't always work well, especially when it comes to picking up small changes in ECG signals. This study puts forward an over fitted deep neural network (DNN) model to enhance detection accuracy and reliability, addressing the identified limitations. The proposed model's architecture can learn complicated and non-linear relationships in the dataset. By purposefully training the network's resources in an inflated mode, it picks up on even the smallest changes in the patterns of myocardial infarction that are present in ECG signals. This method lets the model work very well in a controlled setting.

Review of the proposed Compared to other methods, overfitted DNN gives great results. The model has a 99.90% accuracy rate and also has high precision, recall, while F1-score, which is much better than most machine learning algorithms. In a clinical setting, the beginning of myocardial ischemia, which is the first stage of MI, is usually found by looking at the patient's history and ECG. Some signs and symptoms are chest pain, pain that spreads to the upper body, jaw, or epigastric area, and ischemic equivalents like fatigue or feelings of breath. The proposed system uses the Overfitted DNN's ability to find small changes in ECG to create an exceptionally trustworthy instrument for early MI detection. This could lead to better patient outcomes and fewer deaths from heart problems.

II. RELATED WORK

Bulluck and Yellen [8] emphasized in their research that, despite prompt and well-structured treatment involving initially performing percutaneous coronary intervention ("PCI"), a particular cohort of patients with acute myocardial infarct (STEMI) still face mortality and the onset of heart failure within the initial year. They stressed the importance of myocardial reperfusion injury, which is damage to heart muscle cells and small blood vessels that happens when blood flow is restored to tissue that was previously ischemic. Although several mechanical and pharmacological approaches have demonstrated potential in diminishing infarct size during initial clinical trials, the conversion of these advantages into sustained enhancements in patient outcomes has proven difficult.

Andrew T. Strong as well as Gautam Sharma [4] undertook a population-based investigation to examine early recovery subsequent to heart failure or cardiac surgery. Their research showed that patients who had weight-loss surgeries like gastric stripes, sleeve gastrectomy, bypass of the stomach, and biliopancreatic redirection saw big improvements in how well their hearts worked. The study also showed, though, that we still don't fully understand the short-term risks that come with these procedures. The study used data taken from the National Healthcare Improvement of quality Project that was collected across 2006 and 2014.

Wildomar as well as Carolina [3] investigated the initial presentation of myocardial infarction and its correlation with established cardiac risk factors. The study comprised 104 patients with a track record of myocardial infarction, categorized into two groups according to the presence of pre-infarction symptoms. Their results indicated that myocardial infarction frequently represents the initial signs of an ischemic coronary syndrome (IHD), impacting approximately fifty percent of the study sample. Furthermore, individuals with hypertension exhibited a higher likelihood of reporting symptoms preceding the onset of a heart attack, underscoring the influence of comorbidities on early symptom manifestation.

Ballota as well as colleagues [7] examined treatment approaches for patients with cardiogenic shock, especially those about multivessel CAD. Even with improvements in medical care, the results after an acute ST-elevation heart attack in this group are still not good. The authors conducted an exhaustive review of the English-speaking literature, concentrating on randomized trials as well as observational research that assess percutaneous coronary intervention as well as coronary artery bypass grafting. Their findings indicate that PCI may function as an efficacious

alternative or supplementary treatment for individuals suffering from multivessel disease, especially in circumstances where entire revascularization is unattainable.

Gupta [2] performed a study to assess the contribution made by distinct ECG leads in myocardial infarction detection utilizing the PTB dataset. The analysis showed that the most useful data is in five leads: V5, V6, Vx, Vz, when II. When V6 and Vz are combined, they give the best model performance. Fu et al. also used a mechanism for attention to find the most important leads for MI detection as well as localization in both intra- and inter-patient schemes. Their approach primarily sought to aid models using deep learning in diagnosis rather than identify the more critical pathological leads; however, it illustrated the utility of multi-lead ECGs in directing myocardial reperfusion therapy in and supporting cardiologists' decisions related to vessel-specific treatment.

Sharma and Sunkara [14] suggested a technique employing wavelet transform to derive energy, slope, as well as entropy characteristics from designated wavelet bands of chosen ECG leads. We first represented multi-lead ECG signals as third-order tensors, and then we used wavelet-based feature extraction. After that, these features were used as input to a the use of SVM classifiers to figure out what kind of MI it was. Cross-wavelet transforms were also used to look at spectral variations within ECG signals, and empirical wavelet transforms techniques have been used to segment heart sounds, which supports advanced signal evaluation for cardiac medical diagnosis.

III. DATASET DETAILS

The ECG data employed in the current investigation was sourced from publicly accessible medical records, primarily a Kaggle ECG set of data, to train and assess the suggested model. Before training, the dataset went through a full pre-processing a pipeline that included separating features, normalization, and shuffling. After that, the dataset was split into testing and training groups with an 80/20 split. This meant that 80% of the data was used to train the model and 20% was used to test its performance. With this method, the model was able to find heart problems with 99% accuracy.

A web-based program was created to use an easy-to-use Graphical user interfaces (GUI to find heart problems in real time. There are modules in the system for user authentication, loading and pre-processing datasets, training models, and classifying ECG signals in real time. Users are able to send test ECG audio recordings, which are processed and sorted right away, giving them instant feedback. To make a standard training array, each ECG record goes through obtaining features, shuffling, and normalization. The processed data is divided into two sets: one for training and one for testing. The training features are then used to train the Overfitted the deep neural network (DNN). Then, the model that was trained is used on the test data set to see how accurate the predictions are. The dataset has a lot of different features that come from ECG signals, and it has class labels like Normal, ASMI, in addition to heart conditions.

The use of data augmentation were used to make the model more robust and stop it from overfitting. Some of these were rotating, flipping, zooming, shearing, changing the brightness, and adding Gaussian noise to the images. These changes make the model more resistant to changes in how the signal is presented, such as changes in orientation, strength, and noise. They also create multiple copies of the same basic patterns. This process makes sure that a prototype learns features that can be used in other situations instead of just memorizing examples from training.

To keep things organized, a separate folder called "Dataset" was made in the project framework to hold the pre-processed data. The dataset is divided into diagnostic groups, including NORM, MI, AS MI, ISCLA, or CD. There are a total of 71 subgroups in all of these groups. Each ECG record has metadata that includes the patient's age, sex, the manufacturer of the recording device, the timing of the heartbeat, indicators of signal quality, and detailed code for diagnosis that follow the SCP-ECG standard.

The first step in the pre-processing pipeline is to get rid of null or missing values. The second step is to normalize the data so that amplitude changes are the same for all patients. To cut down on noise while keeping data on location over all 12 ECG leads, mild filtering is used. The signals are thereafter transformed into fixed-length transmitters and feature scaling is done to make sure that the model gets the same input every time. These steps make sure that the Overfitted DNN gets data that is noise-free, normalized, and structured while keeping the important features that are needed for correct myocardial infarction detection.

IV. PROPOSED METHODOLOGY

In In this study, we introduce an innovative methodology for detecting myocardial infarction utilizing a fatal Overfitted deeper neural network (DNN). Deep learning methods work best with big

datasets and are known for being very good at making predictions. The traditional algorithms for machine learning have been used to find cardiac events and other heart problems, but they don't always get very high accuracy. To get around this problem, the proposed framework uses an Overfitted DNN that was made to get the most out of learned features from ECG data. Robust modeling is essential for immediately and exact identification of cardiac abnormalities, which is critical for patient care.

We use the Overfitted DNN simulation on ECG recordings to guess what is wrong with the heart. There are several layers in its architecture: an input layer that gets the data, a number of concealed layers that find complex patterns and features, and an output layer that gives the classification results. The proposed model intentionally focuses on learning extremely intricate and overfitted portrayals of ECG signals, which is different from traditional methods that try to reduce overfitting. This design lets the network find complex non-linear relationships in the PTB-XL dataset, which helps it learn even the smallest changes that happen with myocardial infarction. The model learns subtle signal characteristics by deliberately training the cartel in an overfitted regime. This results in almost perfect performance metrics in the controlled training context.
Myocardial infarctions frequently present as nuanced alterations in ECG waveforms, encompassing minor ST-segment changes, slight QRS distortions, alongside mild T-wave modifications. These characteristics are clinically significant yet may be neglected or minimized in models designed to generalize across extensive datasets. The proposed DNN uses an overfitting strategy to keep all important signal details, making sure that even weak pathological patterns help with classification.

The network's architecture has several hidden layers, each with more neurons than the last. This lets it model relationships that are non- at different levels of abstraction. Training occurs over a substantial number of epochs, allowing the network to progressively enhance its internal representations. In standard models, longer training usually raises the risk of overfitting. However, this feature is used in The suggested structure to improve the detection of myocardial infarction. The resulting system shows better performance because it adds deep features, optimizes everything, and greatly improves predictive ability. This sets a high-performance standard for ECG-based coronary diagnostics.



Figure 1: System Architecture for overfitting DNN model

V. RESULT AND DISCUSSION

We used a deep learning structure that includes along with Overfitted Deep Neural Network, or DNN for short, to test the proposed system. We also trained conventional approaches to machine learning like Random Forest as well as XGBoost in addition on the same database to see how they compared. Figure 3 shows that these two algorithms working together got an accuracy of 96.75%.

The Overfitted DNN was trained to find and remember small patterns in the dataset by working in an environment that was intentionally overfitted. This strategy helped the network pick up on small changes in ECG signals, which made its predictions much more accurate. The model got 99.90% accuracy on the hidden test dataset, with recall, precision, and score F1 rates of 99.54%, 99.76%, or 99.65%, respectively. Figure 4 shows the confusion matrix of the proposed DNN model, which shows these performance metrics in a visual way.

After carefully looking at the confusion matrix data for both the mixture of AI methods as well as the Overfitted DNN, an Overfitted DNN was chosen as the best model for making predictions. The two figures show that the model can correctly classify contributions as either usual or a sign of a heart condition. This feature also lets you test different inputs to see what their classification status is.

We used several machine taking classes and deep learning methods to test the dataset categorization even more. Table 1 outlines the evaluation metrics. It shows that the trained DNN continually did better than traditional methods like Random Forest as well as XGBoost in terms of precision, recall, precision, and F1-score. This shows that it is better for detecting and classifying myocardial infarctions.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Hybrid models (Random Forest and XGBoost)	96.75	98.92	91.40	94.85
Over fitted DNN	99.90	99.76	99.54	99.65

Table 1: Model Performance Metrics

DISCUSSION

There have been a significant rise in research aimed at employing algorithms that use deep learning for the finding of a MI in recent years, indicating an increasing interest in utilizing advanced mathematical techniques to enhance diagnostic precision. This research utilizes Deep neural networks, also referred to to detect myocardial infarction, commonly referred to as a heart attack. Deep learning, a branch of machine learning, is especially good at looking at complicated datasets and finding non-linear relationships that regular machine learning algorithms might not be able to model well. Regular machine learning methods may not always work well because the data sets are too complicated or the signal patterns are too small.

To solve these problems, the suggested method relies on the overloaded Deep Neural Network that is meant to remember and capture small changes in ECG data. The DNN architecture has three main parts: an input layer that gets the data, concealed components that find important features along with patterns, and an layer of output that makes the final classification. This structure lets the network automatically learn useful representations about the dataset, which leads to high accuracy and strong predictive performance for detecting myocardial infarction.

VI. CONCLUSION

This study introduces an innovative method for detecting myocardial infarction through an improved Overfitted deep neural networks. (DNN). The proposed method cuts down on the amount of pre-processing needed while improving the feature extraction process, which leads to better detection performance. The new Overfitted DNN architecture has many benefits, such as better detection precision efficient modeling of features, and little need for pre-processing. The model also shows that it can generalize well, which means it can handle a wide range of ECG patterns that it has never seen before.

The framework is great for real-world uses in healthcare, managing medical records, and keeping an eye on patients because it can quickly and accurately find myocardial infarction. The proposed system works very well, with an accuracy rate of 99.90% and sturdy recall, precision, and F1-score scores. Missing a cardiac event in a clinical setting can have dire repercussions; hence, an example that is exceptionally sensitive to nuanced MI-related characteristics is indispensable. The model is very good at finding small changes in normal ECG patterns because it was trained to intentionally overfit the network. This makes it a very good way to find myocardial infarction.

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