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AI-POWERED HEARTBEAT ANOMALY DETECTION USING CNN & LSTM

Mr. K.JAYA KRISHNA MCA, M Tech., Associate Professor Department of Master of Computer Applications
AVVARU MOHINI LAKSHMI Pursuing M.C.A, QIS COLLEGE OF ENGINEERING & TECHNOLOGY
Vengamukkapalem(V), Ongole, Prakasam dist, Andhra Pradesh- 523272

ABSTRACT:

Cardiac arrhythmia is a condition where heart beat is irregular. The goal of this paper is to apply deep learning techniques in the diagnosis of cardiac arrhythmia using ECG signals with minimal possible data pre-processing. We employ convolutional neural network (CNN), recurrent structures such as recurrent neural network (RNN), long short-term memory (LSTM) and gated recurrent unit (GRU) and hybrid of CNN and recurrent structures to automatically detect the abnormality. Unlike the conventional analysis methods, deep learning algorithms don't have feature extraction based analysis methods.
The optimal parameters for deep learning techniques are chosen by conducting various trails of experiments. All trails of experiments are run for 1000 epochs with learning rate in the range [0.01-0.5]. We obtain five-fold cross validation accuracy of 0.834 in distinguishing normal and abnormal (cardiac arrhythmia) ECG with CNN-LSTM. Moreover, the accuracy obtained by other hybrid architectures of deep learning algorithms is comparable to the CNN-LSTM.

I. INTRODUCTION

Cardiac arrhythmia refers to irregular heart rhythms. According to WHO, 17 million people die annually from cardiovascular diseases. In the US, one in three deaths is related to cardiovascular diseases. Tachycardia is a fast heart rate (above 100 beats per minute), while brady cardia is a slow heart rate (below 60 beats per minute). A trial arrhythmias originate in the atrio ventricular node. A trial fibrillation and a trial flutter are serious arrhythmias that can lead to stroke and heart failure. Conditions like high blood pressure and heart disease can cause these arrhythmias.

Cardiac arrhythmia is a condition where irregular heart rhythms occur. According to World Health Organization (WHO), about 17 million people in the world die every year due to cardiovascular diseases. This is about 31% of the total deaths globally. According to the statistics of American Heart Association (AHA), one out of every three deaths in US is related to cardiovascular diseases. The deaths due to cardiovascular diseases are more than due to all types of cancer and chronic lower respiratory diseases combined. A 2014 study indicates that approximately 2 to 3% of the people in North American and European countries are affected by a trial fibrillation. A heart rate which is high (above 100 beats per minute in adults) is called tachycardia and a heart rate that is slow (below 60 beats per minute) is called brady cardia. If the beat is too early, then it is called premature contraction. Irregular beat is called fibrillation or flutter. Other than the criteria of heart rate, there are a number of other classifications for cardiac arrhythmia depending upon different types of criteria.

Another type of classification is in terms of the site of origin of the irregular heart rate. A trial arrhythmias originate in the a trio ventricular (AV) node. The AV node is positioned between the atria (each of the two upper cavities of the heart from which blood is passed to the ventricles is referred to as atria) and the ventricles. A trial fibrillation (AF), a trial flutter, a trial tachycardia, premature a trial contractions and sinus bradycardia are some examples of a trial arrhythmias. A trial fibrillation and a trial flutter are examples of arrhythmia which may lead to serious consequences. In AF, the atrium is contracted in a very fast and irregular manner with the heart's electrical signals originating from a different part of the atria or in the adjacent pulmonary veins instead of sino-a trial (SA) node. The walls of the atria fibrillate (quiver very fast) instead of beating in a normal way, making atria unable to pump blood properly into the ventricles.

Stroke and heart failure are two complications to which a trial fibrillation can lead to. Conditions like high blood pressure, overactive thyroid gland, coronary and rheumatic heart diseases can lead to AF. A trial flutter has similar symptoms and complications as AF. But in a trial flutter, the advancement of electrical signals of the heart through the atria happens in a fast and regular manner instead of the irregular manner in which it happens in AF.

The a trio ventricular (AV) node. The AV node is positioned between the atria (each of the two upper cavities of the heart from which blood is passed to the ventricles is referred to as atria) and the ventricles. Atrial fibrillation (AF), atrial flutter, atrial tachycardia, premature atrial contractions and sinus bradycardia are some examples of atrial arrhythmias. Atrial fibrillation and atrial flutter are examples of arrhythmia which may lead to serious consequences. In AF, the atrium is contracted in a very fast and irregular manner with the heart's electrical signals originating from a different part of the atria or in the adjacent pulmonary veins instead of sino-atrial (SA) node. The walls of the atria fibrillate (quiver very fast) instead of beating in a normal way, making atria unable to pump blood properly into the ventricles. Stroke and heart failure are two complications to which atrial fibrillation can lead to. Conditions like high blood pressure, overactive thyroid gland, coronary and rheumatic heart diseases can lead to AF. Atrial flutter has similar symptoms and complications as AF. But in atrial flutter, the advancement of electrical signals of the heart through the atria happens in a fast and regular manner instead of the irregular manner in which it happens in AF.

2. SYSTEM ANALYSIS

EXISTING SYSTEM:

The a trio ventricular (AV) node. The AV node is positioned between the atria (each of the two upper cavities of the heart from which blood is passed to the ventricles is referred to as atria) and the ventricles. A trial fibrillation (AF), A trial flutter, A trial tachycardia, premature A trial contractions and sinus brady cardia are some examples of a trial arrhythmias. A trial fibrillation and A trial flutter are examples of arrhythmia which may lead to serious consequences. Cardiac arrhythmia identification involves detecting abnormal heart rhythms through various methods, including electrocardiograms (ECGs), physical examinations, and medical history assessment, to diagnose and understand the underlying causes.

DISADVANTAGES :

1) Less accuracy: The traditional systems for heartbeat anomaly detection often fail to identify subtle irregularities in ECG signals. Due to limitations in feature extraction methods and reliance on handcrafted rules, they produce false positives and false negatives. This reduces their reliability in real-time clinical applications, which can lead to missed diagnoses or unnecessary alarms.

2) Low Efficiency: Existing methods require significant manual preprocessing and are often unable to process large ECG datasets effectively. They struggle with noise, variations in patient data, and high computational costs, making them unsuitable for large-scale or real-time medical monitoring. This low efficiency slows down diagnosis and affects the overall performance of the system.

PROPOSED SYSTEM:

Deep learning techniques are now being increasingly employed in this area. The automated detection of normal and MI was conducted with CNN with an accuracy of 95.22%[4]. An accuracy of 84.54% was achieved in the detection of inferior MI in ECG using CNN[5]. Four types of arrhythmia were classified with an accuracy of 99.38% with MIT BIH data set along with another dataset as input[6]. Classification of MIT Arrhythmia database of ECG into normal and abnormal was conducted using artificial neural network (ANN) achieving an accuracy of 96.77%. There are many works of classifying specific types of cardiac arrhythmia with ECG as normal input data. Often these specific cardiac arrhythmia cases addressed in most of the previous research work will be serious arrhythmia types like myocardial infarction. In short, researches were conducted into classifying normal ECG and many types of arrhythmia affected ECG. Cardiac arrhythmia, though identified by the irregularity in cardiac rhythm, is due to the anomalies happening in the heart. These anomalies cause anatomical differences in the structure of atria and ventricles, thus producing changes in its activation, depolarization and repolarisation. These changes are reflected as deviation of ECG waveform from its normal shape and size.

Deep learning techniques are increasingly used for cardiac arrhythmia detection, achieving high accuracy. Studies have used CNNs to detect

myocardial infarction (MI) with up to 95.22% accuracy and classify arrhythmias with up to 99.38% accuracy. Artificial neural networks (ANNs) have also been used to classify ECGs into normal and abnormal with 96.77% accuracy. Cardiac arrhythmias are caused by heart anomalies, leading to changes in ECG waveforms. These changes can be detected using deep learning techniques, enabling accurate classification of normal and arrhythmia-affected ECGs.

ADVANTAGES :

1) High Accuracy: The integration of Convolutional Neural Networks (CNN) with Long Short-Term Memory (LSTM) networks significantly improves the accuracy of heartbeat anomaly detection. CNN automatically extracts complex features from ECG signals, while LSTM captures temporal dependencies and patterns across time. This combination reduces false positives and false negatives, ensuring more precise diagnosis and reliable identification of anomalies compared to traditional methods.

2) High Efficiency: The proposed CNN–LSTM framework enhances the efficiency of data processing by minimizing the need for manual feature engineering. CNN quickly handles high-dimensional ECG data, while LSTM processes sequential information with reduced computational overhead. As a result, the system can analyze large-scale patient data in real-time, enabling faster decision-making, improved clinical workflows, and suitability for continuous monitoring applications.

3. LITERATURESURVEY& RELATED WORKS

A new pattern recognition method for detection and localization of myocardial infarction using T-wave integral and total integral as extracted features from one cycle of ECG signal.

AUTHORS :

Naser Safdarian, Nader Jafarnia, and Gholamreza Attarod

ABSTRACT:

In this paper we used two new features i.e. T-wave integral and total integral as extracted feature from one cycle of normal and patient ECG signals to detection and localization of myocardial infarction (MI) in left ventricle of heart. In our previous work we used some features of body surface potential map data for this aim. But we know the standard ECG is more popular, so we focused our detection and localization of MI on standard ECG. We use the T-wave integral because this feature is important impression of T-wave in MI. The second feature in this research is total integral of one ECG cycle, because we believe that the MI affects the morphology of the ECG signal which leads to total integral changes. We used some pattern recognition method such as Artificial Neural Network (ANN) to detect and localize the MI, because this method has very good accuracy for classification of normal signal and abnormal signal. We used one type of Radial Basis Function (RBF) that called Probabilistic Neural Network (PNN) because of its nonlinearity property, and used other classifier such as k-Nearest Neighbors (KNN), Multilayer Perceptron (MLP) and Naive Bayes Classification. We used PhysioNet database as our training and test data. We reached over 76% for accuracy in test data for localization and over 94% for detection of MI. Main advantages of our method are simplicity and its good accuracy. Also we can improve the accuracy of classification by adding more features in this method. A simple method based on using only two features which were extracted from standard ECG is presented and has good accuracy in MI localization.

1 .Beat by Beat Classifying Cardiac Arrhythmias with Recurrent Neural Networks.

Authors: Patrick Schwab, Gaetano Scebba, Jia Zhang, Marco Delai, Walter Karlen.

Merits: Introduces a novel RNN architecture for classifying cardiac arrhythmias, achieving an average F1 score of 0.79 on an unseen test set.

Demerits: Limited to single-lead ECG data, which may not capture all arrhythmia patterns.

Reference: arXiv:1710.06319arXiv

2. Detection of Paroxysmal Atrial Fibrillation using Attention-based Bidirectional Recurrent Neural Networks.

Authors: Supreeth P. Shashikumar, Amit J. Shah, Gari D. Clifford, Shamim Nemati.

Merits: Employs attention mechanisms to enhance the detection of paroxysmal atrial fibrillation, achieving an AUC of 0.94.

Demerits: Requires 24-hour Holter ECG recordings, which may not be feasible for all patients.

Reference: arXiv:1805.09133arXiv

3. Cardiac Arrhythmia Detection from ECG with Convolutional Recurrent Neural Networks.

Authors: Jérôme Van Zaen, Ricard Delgado-Gonzalo, Damien Ferrario, Mathieu Lemay.

Merits: Combines convolutional and recurrent layers to detect arrhythmias from single-lead ECG signals, achieving an accuracy of 92.02%.

Demerits: Performance may degrade with noisy or low-quality ECG signals.

Reference: arXiv:2010.03204arXiv

4. A lightweight hybrid CNN-LSTM model for ECG-based arrhythmia detection.

Authors: Negin Alamatsaz, Leyla S. Tabatabaei, Mohammadreza Yazdchi, Hamidreza Payan, Nima Alamatsaz, Fahimeh Nasimi.

Merits: Proposes a lightweight CNN-LSTM model for arrhythmia detection, achieving a mean diagnostic accuracy of 98.24%.

Demerits: May require extensive computational resources for training.

Reference: arXiv:2209.00988arXiv+1ScienceDirect+1

5. ECG-based multi-class arrhythmia detection using spatio-temporal attention-based convolutional recurrent neural network.

Authors: Not specified.

Merits: Utilizes spatio-temporal attention mechanisms to enhance multi-class arrhythmia detection, achieving an average F1 score of 0.835.

Demerits: Complexity may increase with the number of classes and data volume.

Reference: PubMedarXiv+10arXiv+10MDPI+10PubMed+1PubMed+1

6. Automatic cardiac arrhythmias classification using CNN and attention-based RNN network.

Authors: Jie Sun

Merits: Combines CNN and attention-based RNN for arrhythmia classification, achieving an average F1 score of 0.9110.

Demerits: Performance may vary with different datasets and class imbalances.

Reference: Wiley Online LibraryIET ResearchPubMed+2PubMed+2IET Research+2

7. Applying Recurrent Neural Networks for Anomaly Detection in Electrocardiogram Sensor Data.

Authors: Not specified.

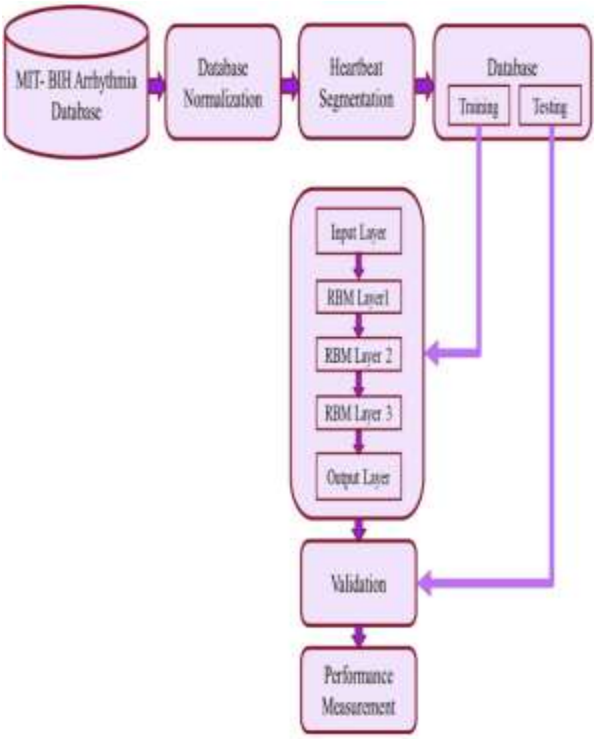
Merits: Applies RNNs for anomaly detection in ECG data, enhancing early detection capabilities.

Demerits: May require large labeled datasets for effective training.

Reference: MDPI Sensors

4. SYSTEM ARCHITECTURE:

The system architecture employs deep learning techniques for cardiac arrhythmia diagnosis. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are utilized. Specifically, Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) architectures are implemented. Hybrid models combining CNN and RNN structures are also explored. The system uses ECG signals as input with minimal data pre-processing. Various experiments are conducted to optimize parameters, including learning rate and epochs. A five-fold cross-validation approach is used to evaluate model performance. The CNN-LSTM architecture achieves an accuracy of 0.834 in distinguishing normal and abnormal ECG signals.



MODULE DESCRIPTION

To implement this project we have designed following modules.

1. Upload Arrhythmia Dataset: using this module we will upload dataset to application.

2. Preprocess Dataset: using this module we will read all dataset values and then replace missing values with MEAN and then normalize training values and then selected important features from dataset by applying PCA algorithm. Dataset contains more than 270 columns and all this columns are not required so by using PCA we selected relevant features from dataset. After features selection we have splitted dataset into train and test where application using 80% dataset for training and 20% for testing.

ALGORITHM:

1. Run LSTM Algorithm: we will input 80% training data to LSTM to trained a model and then model will be applied on 20% test data to perform prediction and then calculate accuracy.

2. Run CNN Algorithm: we will input 80% training data to CNN to trained a model and then model will be applied on 20% test data to perform prediction and then calculate accuracy.

3. LSTM & CNN Training Graph: using this module we will plot CNN and LSTM training graph.

4. Performance Table: using this module we will display both algorithms performance in tabular format.

MODULE:

Data Input Module: Handles ECG signal data with minimal pre-processing.

Deep Learning Module: Implements CNN, RNN, LSTM, and GRU architectures.

Hybrid Model Module: Combines CNN and RNN structures for improved performance.

Parameter Optimization Module: Conducts experiments to find optimal parameters.

Model Evaluation Module: Uses five-fold cross-validation to assess model accuracy.

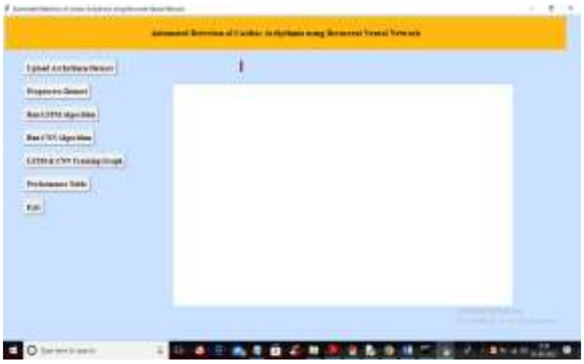
Model Training Module: Trains models using optimized parameters and 1000 epochs.

Model Testing Module: Tests trained models on unseen data.

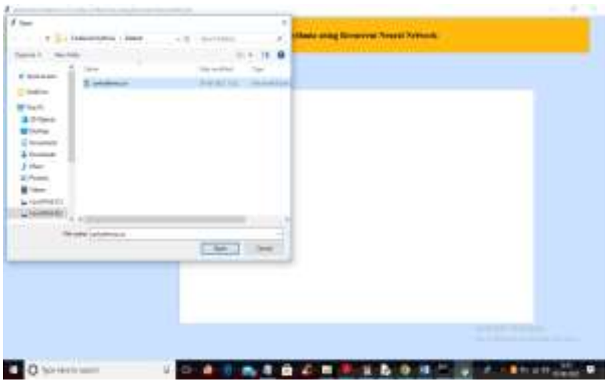
Result Analysis Module: Compares performance of different models and architectures.

5. EXPERIMENTAL RESULTS

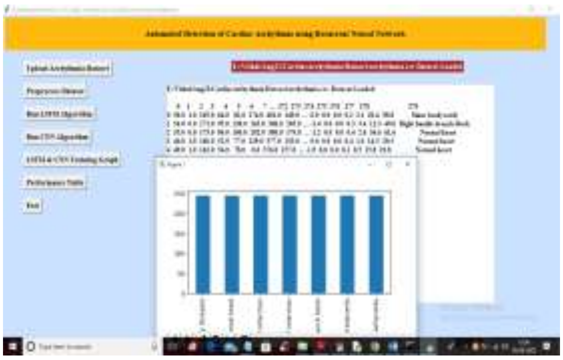
To run project double click on 'run.bat' file to get below screen



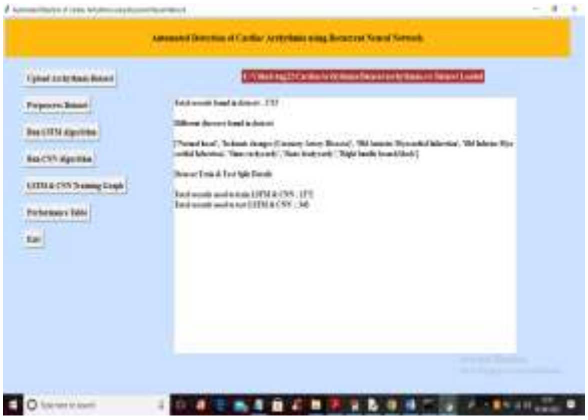
In above screen click on 'Upload Arrhythmia Dataset' button to upload dataset and get below output



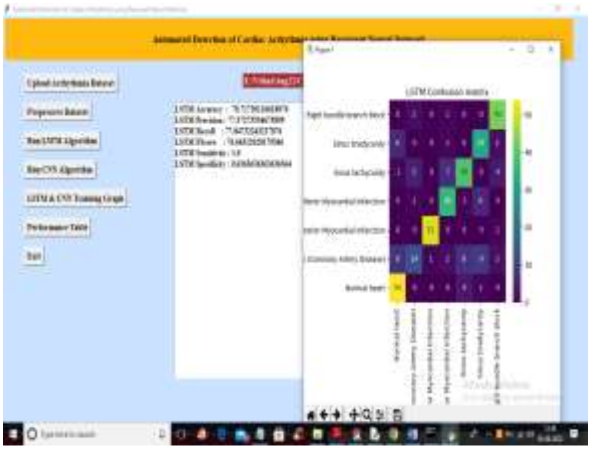
In above screen selecting and uploading 'Arrhythmia' dataset and then click on 'Open' button to load dataset and get below output



In above screen we can see dataset loaded and in graph x-axis represents 7 different disease stages and y-axis represents number of records found for that disease in dataset and in above screen we can see dataset contains some non-numeric values but algorithm accept only numeric values so close above graph and then click on ‘Preprocess Dataset’ button to process dataset and then split into train and test

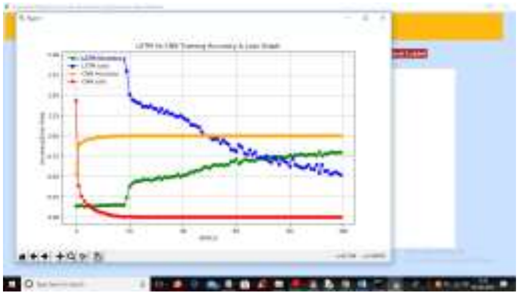


In above screen all dataset converted to numeric format and we can see total dataset size with train and test split details and displaying names of disease and now click on ‘Run LSTM Algorithm’ button to train LSTM with above process dataset and get below output



In above screen with LSTM we got 78% accuracy and in confusion matrix graph x-axis represents Predicted classes and y-axis represents TRUE classes and all blue colour boxes count are wrong prediction and different colour

In above screen with CNN we got 99% accuracy and in confusion matrix graph only 2 counts in blue colour boxes are wrong prediction and rest are correct prediction. Now click on ‘LSTM & CNN Training Graph’ button to get below graph.



In above graph x-axis represents training epoch and y-axis represents training accuracy and loss values and green colour line represents LSTM accuracy and orange colour line represents CNN accuracy and red colour line represents CNN loss and blue line represents LSTM loss and in above graph we can see both algorithms accuracy got increase in every epoch and loss get decrease and now close above graph and then click on “Performance Table’ button to get below output

Dataset Name	Algorithm Name	Accuracy	Precision	Recall	FSCORE	Sensitivity	Specificity
MIT-BIH Dataset	LSTM	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
MIT-BIH Dataset	CNN	[illegible]	[illegible]	[illegible]	[illegible]	1.0	[illegible]

In above screen we can see output metrics of both algorithms in tabular format

6. CONCLUSION AND FUTURE ENHANCEMENT:

Cardiac arrhythmia is basically an irregularity in heart rhythm. Some types of cardiac arrhythmia can lead to complications like stroke, heart attack and may even lead to sudden cardiac death. So, timely detection and diagnosis of arrhythmia is very important. Once arrhythmia is detected, next stage of identification of category of arrhythmia can be done. We developed an automated non-invasive system based on deep learning networks to perform the basic classification of a given ECG data as belonging to normal ECG or abnormal (having arrhythmia) ECG using the most popular publically available MIT-BIH arrhythmia database. We compared the performance using a variety of deep learning architectures of CNN, CNN-RNN, CNN-LSTM and CNN-GRU and obtained an accuracy of 0.834. With concern on computational cost, we are not able to train more complex architecture. The reported results can be further improved by using more complex deep learning architecture. The complex network architectures can be trained by using advanced hardware and following distributed approach in training that we are incompetent to try. We have discussed the role of deep learning techniques such as CNN and recurrent structures in the task of arrhythmia classification. The highlight of the proposed method is that it doesn't need any noise filtering and feature engineering mechanisms. The results obtained prove that the performance of our method is better than other published results in effectively classifying ECG as belonging to normal or arrhythmia class. Though deep learning networks produces excellent results, the disadvantage lies in the insufficient understanding of the complex inner mechanisms of the deep learning networks. This could be overcome by remodelling the nonlinear deep networks to a linear form by computing eigenvalues and eigenvectors in different time steps[20]. The **FUTURE WORK** can be the collection of real world datasets from hospitals having cardiac care units and the application of the same methodologies to the real datasets

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Authors:

Mr. K. Jaya Krishna is an Associate Professor in the Department of Master of Computer Applications at QIS College of Engineering and Technology, Ongole, Andhra Pradesh. He earned his Master of Computer Applications (MCA) from Anna University, Chennai, and his M.Tech in Computer Science and Engineering (CSE) from Jawaharlal Nehru Technological University, Kakinada (JNTUK). With a strong research background, he has authored and co authored over 90 research papers published in reputed peer-reviewed Scopus-indexed journals. He has also actively presented his work at various national and international conferences, with several of his publications appearing in IEEE-indexed proceedings. His research interests include Machine Learning, Artificial Intelligence, Cloud Computing, and Programming Languages. He is committed to advancing research and fostering innovation while mentoring students to excel in both academic and professional pursuits.

AVVARU MOHINI LAKSHMI is a postgraduate student a MCA in the Department if Computer Applications at QIS College of Engineering & Technology, Ongole an Autonomous college in prakasam dist. He completed his undergraduate degree in Degree B.SC(Computers) from ANU His academic interests include Cloud Computing, Artificial Intelligence, Cyber security and Data structures.