



## RECOGNITION OF ECG CONGESTIVE HEART FAILURE USING DEEP LEARNING ALGORITHMS WITH IMAGE PROCESSING TECHNIQUES

<sup>1</sup>Dr.P.Rajendra Prasad, <sup>2</sup>M.PARIMALA, <sup>3</sup>More Praveen

<sup>1</sup>Associate Professor, Department of Computer Science and Engineering, Vignan Institute of Management and Technology for Women, Kondapur, Hyderabad, Mail: [rajipe@gmail.com](mailto:rajipe@gmail.com)

<sup>2</sup>Associate Professor, Department of Computer Science and Engineering, Vignan Institute of Management and Technology for Women, Kondapur, Hyderabad, Mail: [pari.parillu@gmail.com](mailto:pari.parillu@gmail.com)

<sup>3</sup>Assistant Professor, Sreenidhi Engineering college, Department of Computer Science and Engineering, Mail: [praveen48@gmail.com](mailto:praveen48@gmail.com)

### ABSTRACT:

Electrocardiogram (ECG) is an important non-invasive diagnostic method for interpretation and identification of various kinds of heart diseases. In this work, a new Deep Learning (DL) approach is proposed for automated identification of Congestive Heart Failure (CHF) and Arrhythmia (ARR) with high accuracy and low computational requirements. This study introduces, for the first time, a new ECG diagnosis algorithm that combines Convolutional Neural Network (CNN) with the Constant-Q Non-Stationary Gabor Transform (CQ-NSGT). The CQ-NSGT algorithm is investigated to transform the 1-D ECG signal into 2-D timefrequency representation that will be fed to a pre-trained CNN model, called AlexNet. Extracted features with the AlexNet architecture are used as relevant features to be discriminated by a Multi-Layer Perceptron (MLP) technique into three different cases, namely CHF, ARR, and Normal Sinus Rhythm (NSR). The performance of the proposed CNN with CQ-NSGT is compared versus CNN with Continuous Wavelet Transform (CWT), revealing the effectiveness of the CQ-NSGT algorithm. The proposed approach is examined with real ECG records, and the experimental results show the superior performance of the proposed approach over other existing techniques in terms of accuracy 98.82%, sensitivity 98.87%, specificity 99.21%, and precision 99.20%. This demonstrates the effectiveness of the proposed system in enhancing the ECG diagnosis accuracy.

**Keywords:** *Deep learning (DL), Convolutional neural network (CNN), Electrocardiogram (ECG) Arrhythmia (ARR), Congestive heart failure (CHF), Normal sinus rhythm (NSR)*



## **INTRODUCTION:**

An innovative approach to ECG diagnosis by combining Convolutional Neural Networks (CNN) with the Constant-Q Non-Stationary Gabor Transform (CQ-NSGT). This advanced technique aims to enhance the identification of congestive heart failure (CHF) and arrhythmia, two critical cardiac conditions. By integrating the CQ-NSGT, the system extracts intricate temporal and frequency features from the ECG signals, enabling comprehensive analysis. The CNN model further enhances the accuracy and efficiency of the diagnosis process through automated feature extraction and classification. With its user-friendly interface and robust performance, the software system holds great potential to revolutionize ECG analysis, leading to improved patient outcomes and streamlined clinical decisionmaking.

To develop machine learning algorithms for the first time, a new ECG diagnosis algorithm that combines Convolutional Neural Network (CNN) with the Constant-Q Non-Stationary Gabor Transform (CQ-NSGT). The CQNSGT algorithm is investigated to transform the 1-D ECG signal into 2-D time-frequency representation that will be fed to a pre-trained CNN model

**Motivation:** The motivation behind this research is to enhance ECG diagnosis by leveraging the capabilities of deep learning models like CNNs and the time-frequency analysis provided by the CQ-NSGT. ECG signals contain valuable information about heart health, and by transforming them into a 2-D time-frequency representation, more detailed features can be extracted and utilized for accurate diagnosis.

**Constant-Q Non-Stationary Gabor Transform (CQ-NSGT):** The CQ-NSGT is chosen as the transformation technique for the ECG signal. Unlike traditional Fourier Transform, the CQ-NSGT provides a time-frequency representation that adapts to the non-stationary characteristics of ECG signals. It decomposes the 1-D ECG signal into a 2-D representation, capturing both temporal and frequency information.

**Pre-trained CNN Model:** A pre-trained CNN model is used in this algorithm. Pre-training involves training a CNN on a large dataset, typically a general-purpose dataset like ImageNet, to learn general features. By utilizing a pre-trained CNN, the model can leverage the knowledge acquired from the large dataset to extract relevant features from the transformed ECG representation.

**Data Preparation:** A dataset of annotated ECG signals is collected or obtained from previous studies. The ECG signals are pre-processed to remove noise, baseline wander, and other artifacts that could affect the accuracy



of the algorithm. Training and Fine-tuning: The pre-trained CNN model is fine-tuned using the transformed ECG signals generated by the CQ-NSGT. Fine-tuning involves adapting the pre-trained model to the specific task of ECG diagnosis by training it on the annotated dataset. The model learns to extract discriminative features from the 2-D time-frequency representation and make predictions based on those features.

### **LITERATURE REVIEW:**

An assortment of research mechanisms on classifying cardiac arrhythmia from ECG signals can be alienated into two approaches: the non-deep learning approach and the deep learning approach.

The time-honored ML approach uses machine learning algorithms such as Support Vector Machine (SVM), Decision Trees (DTs), and Random Forest (RF) to classify cardiac arrhythmia. For instance, [1] proposed a computational system for diagnosing cardiac arrhythmia using k-nearest neighbor (KNN) and DTs[2]. The model was trained based on 14 features extracted from the MIT-BIH dataset. DTs outperformed KNN with 0.92, 0.96, and 0.86 for accuracy, sensitivity, and specificity, respectively. The authors of [3] detected myocardial infarctions from 10 s ECG signals using SVM. The model was trained using 14 features extracted by the principal component (PCA) technique. The model achieved an overall accuracy of 0.97. The authors of [4] developed a model to detect the narrowing of three types of coronary arteries (CAD). The model is trained with SVM, uses 25 features, and achieves an overall accuracy of 0.95, a sensitivity of 1.00, and a specificity of 0.88. The authors of [5] proposed the Naïve Bayes model to detect five types of cardiac arrhythmias from ECG signals. The best model performance was based on four features extracted using higher-order statistics (HOS). The model obtained an overall accuracy of 0.94, a specificity of 0.67, and a recall of 0.96. In [6], various tree-based ML algorithms, such as Logistic Model Trees, Naïve Bayes Tree, and RF, were trained to classify arrhythmias from 23 recordings and trained to classify 11 classes[7]. The RF scored the best results with an accuracy of 0.97, a specificity of 0.95, and a recall of 0.99. In [8], a genetic algorithm-based back propagation neural network (GA-BPNN) technique for ECG identification was developed to sort out distinct types of arrhythmias with an accuracy of 0.98 [9].

### **METHODOLOGY:**



A new automated CNN deep learning approach for identification of ECG congestive heart failure and arrhythmia using constant-Q non-stationary Gabor transform

In this paper author is building CNN neural network model to predict Congestive Heart Failure (CHF), Arrhythmia (ARR) and Normal Sinus Rhythm (NSR) diseases by analysing ECG (Electrocardiogram) dataset as this dataset is very much important in detecting above diseases. Earlier doctors were using their personal experience to detect diseases from ECG but this technique require lots of experience and time and to overcome from this issue author is training CNN algorithm with above ECG dataset and this trained model can be used to predict diseases from new test data.

In propose work to get better prediction accuracy author is using INBUILT ALEXNET model with the help of transfer learning where ALEXNET last layer will be replace with ECG data to predict diseases. ECG dataset contains single dimensional data and CNN require multidimensional image data so author applying GABOR transformation on ECG data to convert single dimensional data to multi-dimensional data. This GABOR features will be trained with ALEXNET model to predict diseases.

To implement this project author has used ECG dataset which contains 162 records and 65,536 columns and this records contains 3 different types of diseases such as 'ARR', 'CHF' and 'NSR'. In first para you can see full form of each disease and this dataset I saved inside 'Dataset' folder and this dataset is available in MATLAB format so I convert MATLAB file to CSV by using python program called 'MattoCsv.py'.

To implement this project I have designed following modules

- 1) Upload ECG Dataset: Using this module we will upload ECG dataset to application
- 2) Dataset Preprocessing: using this module we will read all ECG records and then normalizing those records to 0 and 1 by diving each values using 255. After normalization we will divide dataset for segmentation
- 3) Segmentation: using this we will segment dataset based on different diseases
- 4) Gabor Image Transformation: using this module we will reshape ECG data to multi-dimensional array and then each array contains ECG signal data and this data will be visualize as image after Gabor transformation.



- 5) **Generate & Load Alexnet Model:** Features extracted from Gabor transformation will be input to Alexnet model to train the model. Generated model can be applied on new test records to classify diseases.

**Disease Classification:** Using this module we will upload test data and then apply Alexnet model and this model will analyse test data to predict diseases as output is showing some records from dataset and each record contains more than 65000 columns. By using Python the kaggle data is processed, python is currently the most widely used multi-purpose, high-level programming language. Python allows programming in Object-Oriented and Procedural paradigms. Python programs generally are smaller than other programming languages like Java. Programmers have to type relatively less and indentation requirement of the language, makes them readable all the time. Python language is being used by almost all tech-giant companies like – Google, Amazon, Facebook, Instagram, Dropbox, Uber... etc. The biggest strength of Python is huge collection of standard library which can be used for the following –Machine Learning, GUI Applications (like Kivy, Tkinter, PyQt etc. ), Web frameworks like Django (used by YouTube, Instagram, Dropbox), Image processing (like Opencv, Pillow), Web scraping (like Scrapy, BeautifulSoup, Selenium), Test frameworks, Multimedia, This study is carried out to check the technical feasibility, that is, the technical requirements of the system. Any system developed must not have a high demand on the available technical resources. This will lead to high demands on the available technical resources. This will lead to high demands being placed on the client. The developed system must have a modest requirement, as only minimal or null changes are required for implementing this system.

#### **Data Collection:**

This is the first real step towards the real development of a machine learning model, collecting data. This is a critical step that will cascade in how good the model will be, the more and better data that we get, the better our model will perform.

There are several techniques to collect the data, like web scraping, manual interventions and etc.

Heart Disease dataset taken from Kaggle (<https://www.kaggle.com/ronitf/heart-disease-uci>)

#### **Dataset:**

The dataset consists of 303 individual data. There are 14 columns in the dataset, which are described below.

1. **Age:** displays the age of the individual.
2. **Sex:** displays the gender of the individual
3. **Chest-pain type(cp):** displays the type of chest-pain **Resting Blood Pressure(trestbps):** displays the resting blood pressure value of an individual in mmHg (unit)



4. ***Serum Cholesterol(chol)***: displays the serum cholesterol in mg/dl (unit)
5. ***Fasting Blood Sugar(fbs)***: compares the fasting blood sugar value
6. ***Resting ECG (restecg)***: displays resting electrocardiographic results
7. ***Max heart rate achieved*** : displays the max heart rate achieved by an individual.
8. ***Exercise,induced,angina***
9. ***ST depression induced by exercise relative to rest***: displays the value which is an integer
10. ***Peak,exercise,ST,segment***
11. ***Number of major vessels (0–3) colored by flourosopy***
12. ***Thal*** :
13. ***Diagnosis of heart disease*** : Displays whether the individual is suffering from heart disease

#### **Data Preparation:**

Wrangle data and prepare it for training. Clean that which may require it (remove duplicates, correct errors, deal with missing values, normalization, data type conversions, etc.)

Randomize data, which erases the effects of the particular order in which we collected and/or otherwise prepared our data

Visualize data to help detect relevant relationships between variables or class imbalances (bias alert!), or perform other exploratory analysis, split into training and evaluation sets

#### **Model Selection:**

We used Decision Tree Classifier machine learning algorithm, We got a accuracy of 96.7% on test set so we implemented this algorithm.

#### **RESULT ANALYSIS:**



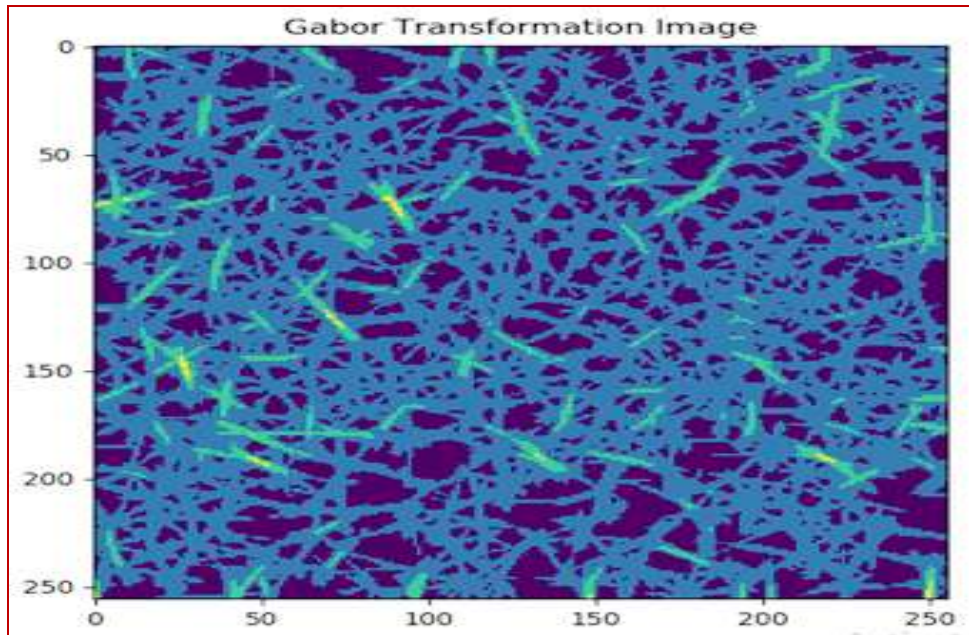


Figure: Converting ECG data to signal images

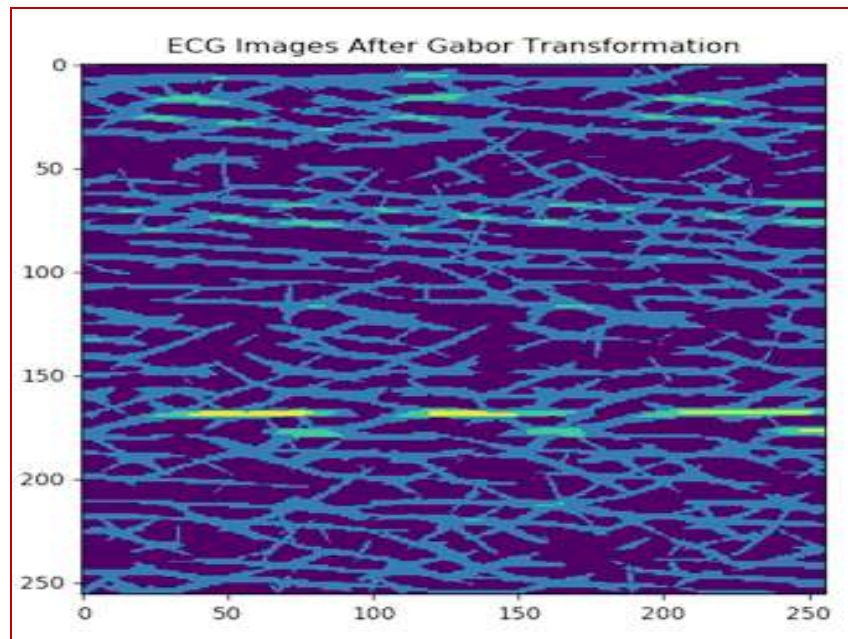


Figure: GABOR successfully applied on ECG data

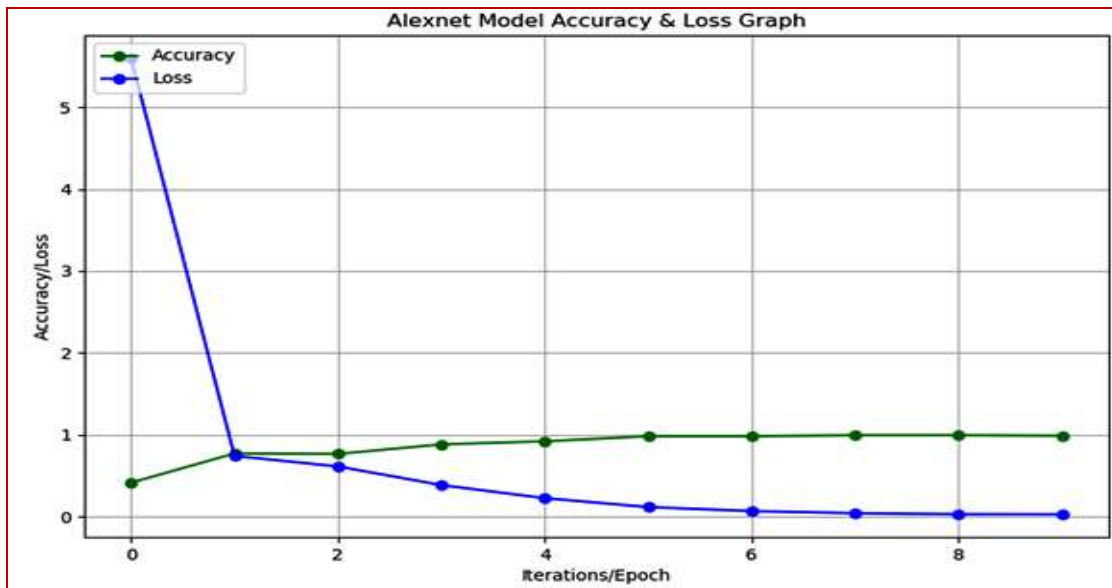


Figure: Alexnet accuracy and loss

## CONCLUSION:

New automated DL approach is proposed for ECG multiclass diagnosis of CHF, ARR, and NSR with high accuracy. The proposed ECG diagnosis system investigates the CQ-NSGT algorithm for transforming the input 1-D ECG signal into 2-D time-frequency representation which will be fed to the pre-trained AlexNet CNN architecture. To the authors' knowledge, it is the first time to combine the proposed CQ-NSGT algorithm with a pretrained CNN architecture in one fully automated diagnosis system that results in highly accurate ECG multiclass classification using low to medium hardware requirements. The effectiveness of the proposed diagnosis system is demonstrated by investigating several ECG records representing different cases of patient age and patient gender from the MIT-BIH and BIDMC databases. The performance of ECG classification for the three cardiac conditions CHF, ARR, and NSR is evaluated in terms of ACC, Se, SP, and Pr. The average classification results using 5-fold cross-validation are obtained in order to validate the results of the proposed system. Experimental results reveal that the proposed approach achieves high diagnosis performance with overall average ACC of 98.82%, Se of 98.87%, SP of 99.21%, and Pr of 99.20%. The proposed approach is also compared with other recent diagnosis systems, and the results reveal the superior performance of the proposed system as shown in Table 5. The AlexNET architecture is compared with other CNN deep models, including VGG-16, VGG-19, ResNet-50, ResNet-101, Inception-v3, and DenseNet, and the





results are shown in Table 6. Results reveal that the AlexNET model outperforms other CNN architectures by achieving the highest classification results and taking the shortest processing time. The highest classification performance of AlexNet architecture over other deep models comes from the fact that the 2-D signal resulted from ECG transformation is a relatively simple image, so there is no need to have a depth layer in the CNN architecture. The use of deep layers leads to an increase in the free parameters, which can cause over-fitting and performance degradation. Note that for large-scale datasets such as ImageNet, deeper networks outperform shallow ones because the data is diverse, and the networks learn abstractions for a huge selection of classes. On contrast, in ECG classification, the data variability is several orders of magnitude smaller than image classification problems, and therefore deeper networks are not efficient for ECG classification. The AlexNet architecture has a faster convergence rate and better training performance than other deep CNN architectures. This reveals the high computational efficiency of the AlexNet architecture for ECG diagnosis systems.

#### **REFERENCES:**

- [1] K. Graves, Ceh: Official certified ethical hacker review guide: Exam 312-50. John Wiley & Sons, 2007.
- [2] R. Christopher, "Port scanning techniques and the defense against them," SANS Institute, 2001.
- [3] Swamy, S. Ranga, et al. "Dimensionality reduction using machine learning and big data technologies." *Int. J. Innov. Technol. Explor. Eng.(IJITEE)* 9.2 (2019): 1740-1745..
- [4] Rashmi T V. "Predicting the System Failures Using Machine Learning Algorithms". *International Journal of Advanced Scientific Innovation*, vol. 1, no. 1, Dec. 2020, doi:10.5281/zenodo.4641686.
- [5] S. Robertson, E. V. Siegel, M. Miller, and S. J. Stolfo, "Surveillance detection in high bandwidth environments," in *DARPA Information Survivability Conference and Exposition*, 2003. Proceedings, vol. 1. IEEE, 2003, pp. 130–138.
- [6] Sirisati, R., Kumar, C.S., Latha, A.G., Kumar, B.N. and Rao, K., 2021. Identification of Mucormycosis in post Covid-19 case using Deep CNN. *Turkish Journal of Computer and Mathematics Education (TURCOMAT)*, 12(9), pp.3441-3450..



- [7] Swamy, S. R., Praveen, S. P., Ahmed, S., Srinivasu, P. N., & Alhumam, A. (2023). Multi-Features Disease Analysis Based Smart Diagnosis for COVID-19. *Computer Systems Science & Engineering*, 45(1).
- [8] L. Sun, T. Anthony, H. Z. Xia, J. Chen, X. Huang, and Y. Zhang, "Detection and classification of malicious patterns in network traffic using benford's law," in Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC), 2017. IEEE, 2017, pp. 864–872.
- [9] Sirisati RS, Kumar CS, Latha AG, Kumar BN, a Rao KS. An Enhanced Multi Layer Neural Network to Detect Early Cardiac Arrests. In 2021 5th International Conference on Electronics, Communication and Aerospace Technology (ICECA) 2021 Dec 2 (pp. 1514-1518). IEEE.