# Analyzing Clinical 12-Lead ECG Images Using Deep Learning Algorithms for Objective Detection of Cardiac Diseases

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***Abstract*—Electrocardiogram (ECG/EKG) is the most common method for the study and detection of cardiovascular diseases. Current clinical ECG devices generate 12-lead ECG traces as images on paper. The majority of artificial intelligence (AI) algorithms created for automated cardiac monitoring are based on ECG data, which necessitates brand-new, expensive equipment that the majority of clinics cannot afford. In this paper, we propose a novel method of using deep learning (DL) techniques to analyze clinical 12-lead ECG images for the objective detection of cardiac diseases. A convolutional neural network (CNN) is a DL technique that uses 2D images as input and convolves them with various filters to produce the required outputs. CNNs can be trained with enormous datasets and millions of parameters. This work introduces a high-performance CNN-based method for the objective diagnosis of heart disorders in ECG images. The proposed model automatically learns a suitable feature representation from raw clinical ECG images and thus negates the need for hand-crafted features. The ECG image dataset of 929 distinct patient records, which contains 12 lead ECG information of different cardiac patients from the Mendeley Database, was used to evaluate the classification performance. Before being analyzed by CNN, all clinical ECG waveform images were converted into two formats: colorful and grayscale images. The proposed system achieved a maximum of 97% accuracy and 96% sensitivity for colored images and 98% accuracy and 97% sensitivity for grayscale images. To validate the result, we classified the images by using dense artificial neural networks (dense ANN) and compared the results with our CNN results and CNN significantly improved the accuracy. As this proposed method is highly accurate and does not economically burden clinics, it can potentially be used as a clinical auxiliary diagnostic tool and effectively optimize medical resources.**

**Keywords: Cardiac disease detection, clinical ECG equipment, CNN, dense ANN, ECG images, Electrocardiogram (ECG/EKG).**

## I. Introduction

The electrocardiogram (ECG/EKG) is a ubiquitous tool in modern clinical medicine that has been used by cardiologists and non-cardiologists for decades. ECG analysis offers various windows into the physiological and anatomical health of the heart but can also provide helpful diagnostic hints for illnesses that are systemic in nature [1]. Most clinics' current clinical ECG machines print out 12-lead ECG traces as images. ECG data is the foundation for the majority of AI algorithms created for automated heart monitoring. Automatic detection of ECG data is a promising research area, but this requires new equipment for ECG data collection. Most medical facilities, especially at rural, remote, or community-level clinics, cannot afford to upgrade current ECG equipment. Thus, implementing ECG analysis from data is a very expensive proposition for most clinics. To reduce this economic burden on clinics, we propose an artificial intelligence (AI) algorithm that can process the currently available ECG images from clinical 12-lead ECG equipment. The accuracy of the automatic analysis of images can be improved by using deep learning (DL) for detecting cardiac diseases.

Image processing and classification have gained popularity in the AI fields of today's technology. Image processing involves basic operations, namely image restoration and rectification; image enhancement; image classification; image fusion, etc. The automatic categorization of images into several classifications is the goal of image classification [2]. Two types of classification are supervised classification and unsupervised classification. The process of image classification involves two steps; training of the system followed by testing [3]. The training process means taking the characteristic properties of the images (form a class) and forming a unique description for a particular group. Depending on the binary or categorical nature of the classification problem, the operation is carried out for all groups. In the testing phase, the test images are categorized according to the several classes for which the system has been trained. This class assignment is based on the division of classes using the training features.

The ECG waveform, which represents the electrical activity of the heart, is crucial in the diagnosis of heart illnesses because it can identify any abnormalities in heart rhythm, rate, or morphology. ECG signals are mainly composed of QRS wave groups, P waves, T-waves, and other main waveforms. Different wave bands represent different cardiac activities, which is an important basis for analyzing ECG signals. For several reasons, the automatic classification of ECG signals is a challenging problem. Different patients' basic ECG patterns may exhibit differences in their morphological and temporal properties in their ECG waveforms. The ECG waveforms may be the same for one patient at one time while another patient has a different heartbeat, or they may diverge. In clinical ECG trace waveform image classification, deep learning has come a long way. Deep Learning is defined as a class of machine learning techniques that uses numerous layers of nonlinear information processing for supervised or unsupervised feature extraction, transformation, and classification as well as pattern analysis [4]. Images of clinical ECG traces make a great foundation for deep-learning AI applications. The ECG is a commonly used tool that produces reproducible raw data that is simple to store and send in digital format. A deep-learning algorithm is fed these images of clinical ECG recordings.

Different techniques have been applied to the basic sequential steps of ECG pattern classification, including preprocessing, feature extraction, and classification. Among the most recent published works are those as follows. An automated ECG beat classification system using convolutional neural networks has been presented in [5]. The proposed model automatically learns a suitable feature representation from raw clinical ECG trace images and thus negates the need for hand-crafted features. By using small and patient-specific training data, the proposed system efficiently classifies ECG beats into five different classes recommended by the Association for Advancement of Medical Instrumentation (AAMI) and achieves significant classification accuracy and computational efficiency for ECG signal classification. Another improved classifier used in automatic diagnostic systems for the classification of ECG arrhythmias has been presented in [6] which achieved an accuracy of 99%. This diagnostic system consists of a combined fuzzy clustering neural network algorithm for the classification of ten types of arrhythmias obtained from the MIT-BIH database. In [7], an improved model based on a 1D convolution neural network (CNN) is proposed to classify ECG signals. This model enables the classification of 5 typical kinds of arrhythmia signals by extracting the effective features from the original data and classifying the features automatically on the public MIT-BIH arrhythmia database.

In this study, we propose a DL-based clinical ECG image classification system for the objective detection of cardiac diseases using CNN. In most hospitals and clinics worldwide, 12-lead ECG records are being recorded in image format directly from the ECG equipment. Manual processing of these paper-based ECG records would require trained cardiologists and would be very time-consuming. The suggested approach extracts meaningful features, eliminating the requirement for manual feature extraction and pre-processing, to simplify and streamline this procedure. In order to assess the effectiveness of our suggested model, 929 unique patient ECG records from the Mendeley Database that contain 12 lead ECG data were used. The proposed system was compared with dense artificial neural networks (dense ANN) to validate the results. To evaluate the performance of both DL models in identifying the images, the models' accuracy and sensitivity are provided. By making cardiologists and other medical professionals aware of this information, the first step in improving healthcare can be taken.

## II. Methods

### A. ECG Waveform Images

In this work, we have experimented with a clinical ECG waveform image set of cardiac patients, which was created under the auspices of Ch. Pervaiz Elahi Institute of Cardiology Multan, Pakistan, aims to help the scientific community to conduct research for cardiovascular diseases [8]. There are 4 sections of different waveform groups of ECG images. They can be assembled as

1) ECG waveform images of Myocardial Infarction (MI) patients (240),
2) ECG waveform images of patient that have abnormal heartbeat (233),
3) ECG waveform images of patient who have history of MI (172), and
4) ECG waveform images for healthy subjects (284).

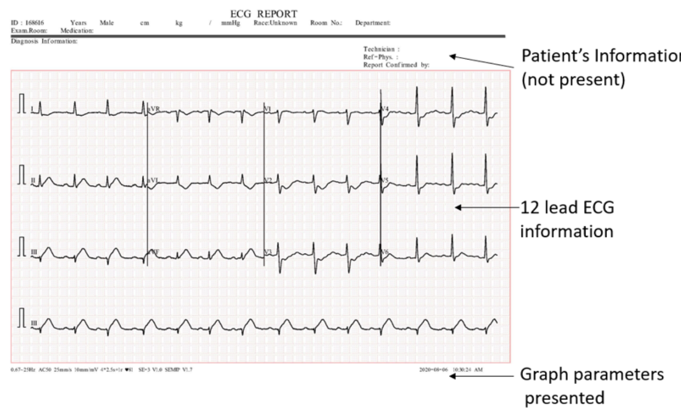


Fig. 1. Example of a 12-lead ECG image from a clinical ECG equipment. Alphanumeric values (demographic information, ECG parameter values, and interpretation) are located in the upper part of the report. Waveform image is given as time series graphs with a grid, covering the middle and lower part of the report, smallest units are 25mm/s and 10 mm/mV.

An ECG report typically contains both alphanumeric values and waveform graphs, which are shown in Fig. 1. The upper part of the ECG report is a list of alphanumeric values including demographic information, patient ID, evaluation date, ECG parameters, and interpretations (e.g., normal sinus rhythm). Demographic information refers to basic patient information, including name, age, sex, and ethnicity [which is not included in these datasets]. ECG parameters include ventricular rate, PR interval, QRS duration, QT/QTc, and P-R-T axes [9]. The waveform graphs, which typically cover the middle and bottom part of the ECG, are time series graphs representing the sensor measurement data. This is explained in Fig. 1:

We have processed these images such that we have deleted the alphanumeric values and only kept the part where the ECG waveforms are. These were 2-dimensional objects that were then trained with a deep learning algorithm to classify them into categories. After that, we converted these images into grayscale images by using the IrfanView tool, which is one-dimensional, and worked with a deep learning algorithm on these images to classify them. Examples of colored and grayscale images are shown in Fig. 2.

### B. CNN Algorithm

Computational models of neural networks have been around for a long time (Fig. 3). Neural networks are made up

Fig. 2. A representative example of processed images that are suitable for the CNN deep learning model. Each image has a dimension of 670 390 pixels (from raw ECG images of a Myocardial Infarction patient) a) A Colored image where there are 3 channels of RGB information, and b) A Grayscale image where there is only one channel.

of several layers, with each layer connected to the other layers, forming the network. CNN is a variant of Multi-Layer Perceptron (MLPs), which is inspired by biology. The CNN architecture has shown excellent performance in many computer vision and machine learning problems due to its highly satisfactory performance. The CNN model integrates two main parts of the ECG pattern recognition system—feature extraction and classification. Linear algebra is the basis for how these CNNs work. Matrix vector multiplication is at the heart of how data and weights are represented [10]. Each of the layers contains a distinct set of characteristics for an image set. For instance, if a face image is an input into a CNN, the network will learn some basic characteristics such as edges, bright spots, dark spots, shapes, etc. in its initial layers. The next set of layers will consist of shapes and objects relating to the image which are recognizable, such as eyes, nose, and mouth. The subsequent layer consists of aspects that look like actual faces, in other words, shapes, and objects that the network can use to define a human face. CNN matches parts rather than the whole image, therefore breaking the image classification process down into smaller parts (features).

A 3x3 grid is defined to represent the feature extraction by the CNN for evaluation. The process, known as filtering, involves lining up the feature with the image patch. One-by-one, each pixel is multiplied by the corresponding feature pixel, and once completed, all the values are summed and divided by the total number of pixels in the feature space [11]. The final value for the feature is then placed into the feature patch. This process is repeated for the remaining feature patches, followed by trying every possible match— repeated application of this filter, which is known as a convolution. The next layer of a CNN is referred to as ”max pooling”, which involves shrinking the image stack. To pool an image, the window size must be defined (e.g., usually 2x2/3x3 pixels), and the stride must also be defined (e.g., usually 2 pixels). The window is then filtered across the image in strides, with the max value being recorded for each window. Max pooling reduces the dimensionality of each feature map whilst retaining the most important information. The normalization layer of a CNN also referred to as the rectified linear unit (ReLU), involves changing all negative values within the filtered image to 0. This step is then repeated on all the filtered images. The ReLU layer increases the non-linear properties of the model [12]. For the output layer, we can have 2 types of activation: softMax and sigmoid, but for CNN, SoftMax is used most often.

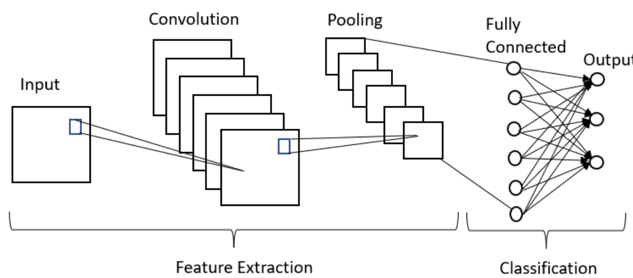


Fig. 3. CNN basic structure

### C. Dense ANN Algorithm

Artificial Neural Networks (ANN) are relatively crude electronic models based on the neural structure of the brain. ANN is an imitation of the natural neural network where the artificial neurons are connected in a similar fashion to the brain network. An artificial neural network consists of processing units called neurons. An artificial neuron tries to replicate the structure and behavior of a natural neuron. A neuron consists of an input (dendrites) and one output (synapse via axon). The neuron has a function that determines the activation of the neuron.

The dense ANN architecture comprises of:

1) *Input layer:* Receives the input values.
2) *Hidden (Dense) layer(s):* A dense or hidden layer is a layer that is deeply connected with its preceding layer, which means the neurons of the layer are connected to every neuron of its preceding layer. The hidden layers can be thought of as individual feature detectors, recognizing more and more complex patterns in the data as it is propagated through the network. For dense ANN, there are more than one dense layer which are responsible for creating features. A layer is ”hidden”

in the sense that it does not connect to the outside world; the input and output layers take care of this. The neurons in any given layer are only connected to the next layer. The numbers of layers and nodes within each layer are variable and the hyper parameters of the model are selected by the practitioner.

3) *Output layers:* There can be single or multiple output layers. Usually it has one neuron, and its output ranges between 0 and 1, that is, greater than 0 and less than 1. But multiple outputs can also be present [13].

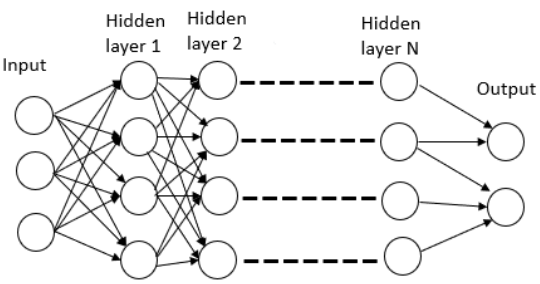


Fig. 4. Dense ANN model basic structure with N hidden layers

Basically, all dense artificial neural networks have a similar structure or topology as shown in Fig. 4. In that structure, some of the neurons interface with the real world to receive its inputs. The network's outputs are provided to the outside world by other neurons. This output might be a particular character that the network thinks it has scanned or the particular image it thinks is being viewed. Once a network has been structured for a particular application, it is ready to be trained. To start this process, the initial weights are chosen randomly. Then, the training, or learning, begins [14]. ANN has a very good ability to learn how to do tasks based on the data given for training or initial experience. All the rest of the neurons are hidden from view.

## III. Results

### A. Training the Datasets

In this paper, we chose to work with 4 types of clinical ECG waveform images of cardiac patients' records to fit them in CNN and dense ANN algorithms to make detection and classification.Images were processed in normal scale and also converted to grayscale while preserving all signal information. The original dimensions of the images were 760 x 390. After formatting the images, we trained our CNN model with our datasets. We followed two different algorithms to train our data. These 2 dataset split groups are as follows:

1) *Dataset with 80/20 split:* Here we have divided the dataset into 2 groups as training and testing set, where 80 percent images are kept in training set and other 20 percent images are kept in testing set.
2) *Dataset with 70/15/15 split:* The whole dataset has been separated into three groups here for training, validation, and testing, with 70% of the images remaining in the training set, 15% remaining in the validation set, and the last 15% remaining in the testing set.

TABLE I
Key Parameter List Of CNN and Dense ANN deep learning model

| **CNN** |
|---|
| Convolution (Input) Layer |
| Dense (Output) Layer |
| Epoch size (number of iterations the Model will run) |
| Batch Size |
| Activation Layer |

| **Dense ANN** |
|---|
| Dense Layer |
| Epoch size (number of iterations the Model will run) |
| Batch Size |
| Activation Layer |

In the CNN model, there are different sets of parameters that affect the accuracy level of our model. The parameters can be listed as the following Table I. We have adjusted the parameters in several settings and run the model with them in order to improve the accuracy of our CNN model. For instance, we left the batch size at 32 in the first setup, which implies that the model takes 32 images in a single batch. We experimented with several setups in this part to find the one that would provide the model with the most accuracy.

### B. CNN Model Results

To train our CNN model with the optimum parameter variation configuration, two datasets with splits of 80/20 and 70/15/15 on normal images and grayscale images were used. We also examined the effectiveness of our model using 10-fold cross-validation. Cross-validation is a statistical method used to estimate the skill of machine learning models. Cross-validation allows models to be tested using the full training set by means of repeated resampling, thus maximizing the total number of points used for testing and, potentially, helping to protect against overfitting.

The $k$-fold cross-validation estimator has a lower variance than a single hold-out set estimator, which can be very important if the amount of data available is limited [15]. If you have a single hold out set, where 80% of the data is used for training and 20% is used for testing, the test set is very small. Therefore, the performance estimate will vary significantly for various data samples or for various data divisions to create training and test sets. $K$-fold validation reduces this variance by averaging over $k$ different partitions, so the performance estimate is less sensitive to the partitioning of the data. In this paper, we have used the value of $k$ as 10 so it will take the testing samples in 10 validations. The accuracy we obtained for both normal and grayscale images is 97 and 98 percent, respectively, as shown in Table II and Table III, which exhibit the parameter settings and primary outcomes of both algorithms.

In Fig. 5 and Fig. 6, we can compare the model parameter values and major outcomes for the training and validation sets, for the dataset with 80/20 split and the dataset with 70/15/15 split. We attempted to use the CNN model for detecting one test image and trying to fit that into any classes that we were

TABLE II
RESULTS OF CNN MODEL ON COLORED AND GRAY SCALES IMAGES FOR DATASET WITH 80/20 SPLIT

| | **Dataset with 80/20 split Normal distribution** | | **Dataset with 80/20 split-10-fold cross validation** | |
|---|---|---|---|---|
| **Parameter** | **Colored image set** | **Gray scale image set** | **Colored image set** | **Gray scale image set** |
| Input layer | 4 layers (16 -32-16-64) | 4 layers (16 -32-16-64) | 4 layers (16 -32-16-64) | 4 layers (16 -32-16-64) |
| Epoch | 20 | 15 | 20 | 15 |
| Dense layer | 512 | 100 | 512 | 100 |
| Batch size | 32 | 32 | 32 | 32 |
| Activation | Relu+ softmax | Relu+ softmax | Relu+ softmax | Relu+ softmax |
| Accuracy | 94 | 100 | 97 | 100 |
| Sensitivity | 93 | 100 | 97 | 100 |

TABLE III
RESULTS OF CNN MODEL ON COLORED AND GRAY SCALES IMAGES FOR DATASET WITH 70/15/15 SPLIT

| | **Dataset with 70/15/15 split Normal distribution** | | **Dataset with 70/15/15 split 10-fold cross validation** | |
|---|---|---|---|---|
| **Parameter** | **Colored image set** | **Gray scale image set** | **Colored image set** | **Gray scale image set** |
| Input layer | 4 layers (16 -32-16-64) | 5 layers (16-32-16-32 -64) | 4 layers (16 -32-16-64) | 5 layers (16-32-16-32 -64) |
| Epoch | 20 | 25 | 20 | 25 |
| Dense layer | 512 | 512 | 512 | 512 |
| Batch size | 32 | 32 | 32 | 32 |
| Activation | Relu+ softmax | Relu+ softmax | Relu+ softmax | Relu+ softmax |
| Accuracy | 97 | 97 | 97 | 98 |
| Sensitivity | 96 | 97 | 97 | 97 |

using after setting up the optimal parameter settings for the model. When a new patient enters a hospital, we can compare the ECG record to our algorithm. We can categorize that new clinical scan using our model in order to find their disorders. By analyzing Table II and Table III We can choose which setup to employ while classifying and processing images in order to identify the patients' disease patterns.

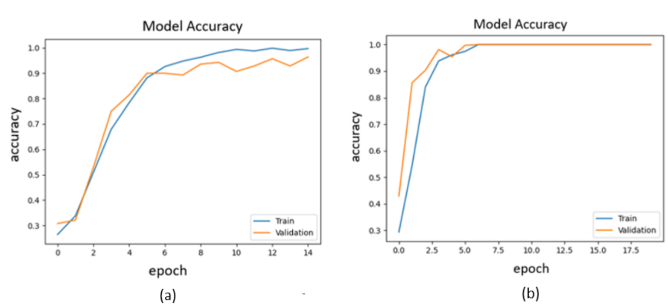


Fig. 5. CNN Model accuracy comparison for Dataset with 80/20 split a) colored images b) gray scale images

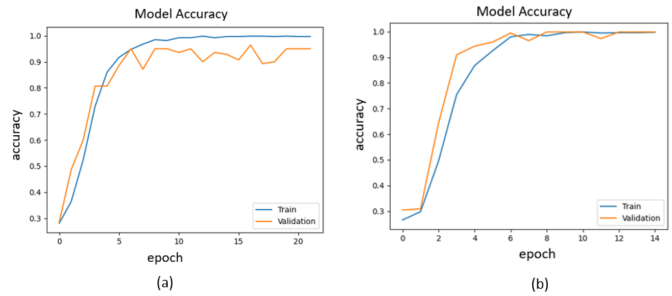


Fig. 6. CNN Model accuracy comparison for Dataset with 70/15/15 split a) colored images b) gray scale images

## C. Dense ANN Model Results

We have once more trained our model with an ANN model in order to compare the findings of our CNN with those of another model and to see how our datasets are acting (Fig. 7 and Fig. 8). To acquire the best results for our photos in this situation, we trained our model for both normal division and *k*-fold cross-validation.

TABLE IV
RESULTS OF DENSE ANN MODEL ON COLORED AND GRAY SCALES IMAGES FOR DATASET WITH 80/20 SPLIT

| | **Dataset with 80/20 split-Normal distribution** | | **Dataset with 80/20 split-10-fold cross validation** | |
|---|---|---|---|---|
| **Parameter** | **Colored image set** | **Gray scale image set** | **Colored image set** | **Gray scale image set** |
| Dense layer | 1024, 512 | 1024, 512 | 2000, 1000 | 2000, 1000 |
| Epoch | 100 | 100 | 100 | 100 |
| Batch size | 32 | 32 | 32 | 32 |
| Activation | Relu+ softmax | Relu+ softmax | Relu+ softmax | Relu+ softmax |
| Accuracy | 91 | 93 | 93 | 94 |
| Sensitivity | 90 | 93 | 93 | 94 |

To find the model's optimal configuration, we adjusted the model's parameter values and trained it. Table IV and Table V display the accuracy we ultimately obtained, which is 93% for both colored and grayscale images. We can compare the accuracy results for the training and validation sets for both the dataset with an 80/20 split and the dataset with a 70/15/15 split in Fig. 7 and Fig. 8, respectively.

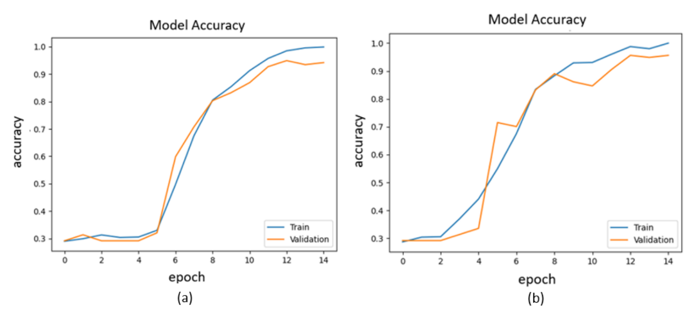


Fig. 7. Dense ANN Model accuracy comparison for Dataset with 80/20 split a) colored images b) gray scale images

TABLE V
RESULTS OF DENSE ANN MODEL ON COLORED AND GRAY SCALES IMAGES FOR DATASET WITH 70/15/15 SPLIT

| | **Dataset with 70/15/15 split -Normal distribution** | | **Dataset with 70/15/15 split -10-fold cross validation** | |
|---|---|---|---|---|
| **Parameter** | **Colored image set** | **Gray scale image set** | **Colored image set** | **Gray scale image set** |
| Dense layer | 1024, 512 | 1024, 512 | 1024, 512 | 1024, 512 |
| Epoch | 100 | 100 | 100 | 100 |
| Batch size | 32 | 32 | 32 | 32 |
| Activation | Relu+ softmax | Relu+ softmax | Relu+ softmax | Relu+ softmax |
| Accuracy | 93 | 94 | 93 | 94 |
| Sensitivity | 93 | 94 | 94 | 94 |

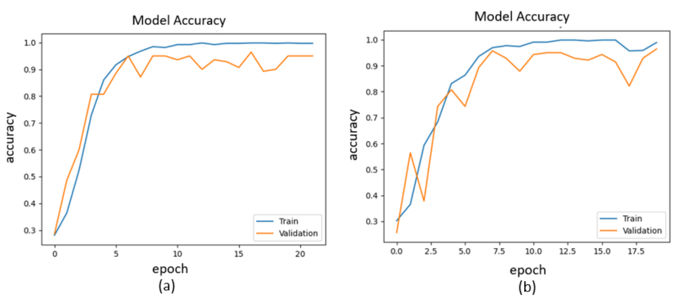


Fig. 8. Dense ANN Model accuracy comparison for Dataset with 70/15/15 split a) colored images b) gray scale images

## IV. DISCUSSION

We can compare the accuracy outcomes of the CNN and ANN models from the tables and figures up above. We can see that the CNN model performs better when training the images for the classification of our image dataset. The accuracy of the CNN model was up to 98%, compared to 93% for the dense ANN model. The CNN model performs better in our studies for datasets with an 80/20 split and with a 70/15/15 split in all aspects of colored and grayscale images.

Feature extraction is a key step in ECG classification. The computational complexity of the overall pattern recognition process may increase with the use of feature extraction methods with preprocessing and postprocessing techniques like normalization, segmentation, dimensionality reduction, and feature selection, making them unsuitable for small wearable health monitoring devices. Thus, in order to mitigate the aforementioned limitations and drawbacks, we used the CNN model to classify our images. In CNN, the model automatically extracts the features from the input 2D images and classifies the images. However, in dense ANN, ANN uses a 1D version of the images to extract the features, which makes the computational process exceedingly difficult and time-consuming. In the testing stage, ANNs lose some of their potential external validity, which lowers their total accuracy. This explains why the performance of ANNs may not live up to expectations in the absence of systems capable of choosing appropriate variables holding pertinent information. CNN performs better in classifying the clinical ECG waveform traces as a result of this complexity.

In [5], for image classification, the overall performance of the proposed approach shows a validation set accuracy of 96.4% and a test set accuracy of 92.7%. For 2D clinical ECG waveform images as input, our proposed CNN model exhibits accuracy as high as 98% and sensitivity as high as 97%. In [13], their ANN model had an accuracy rating of 85%, but our proposed model has an accuracy rating of 93% and a sensitivity rating of 93%, which is a considerably higher performance for image classification for a dense ANN model.

## V. CONCLUSION

This paper proposes a method for categorizing and detecting various illness categories from clinical 12-lead ECG image datasets of cardiac patients utilizing DL approaches (e.g., CNN and dense ANN models). We have demonstrated the feasibility with normal (colored) and gray-scale images and compared these two types of datasets. On both datasets, it was discovered that the accuracy of the CNN model was the highest. This CNN model is capable of identifying and categorizing heart disorders from a single 12-lead ECG image. Since most medical hospitals and clinics use ECG images, utilizing deep learning to detect and identify the ECG data will help us diagnose cardiac patients without placing a financial strain on these healthcare facilities and may be simpler to adopt.


## ACKNOWLEDGMENT

This material is based upon work supported by the National Science Foundation under Grant No. 1932281.


## REFERENCES


[1] Siontis KC, Noseworthy PA, Attia ZI, Friedman PA. Artificial intelligence-enhanced electrocardiography in cardiovascular disease management. Nat Rev Cardiol. 2021 Jul;18(7):465-478. doi: 10.1038/s41569-020-00503-2. Epub 2021 Feb 1. PMID: 33526938; PMCID: PMC7848866.

[2] Lillesand, T.M. and Kiefer, R.W. and Chipman, J.W., in "Remote Sensing and Image Interpretation" 5th ed. Wiley, 2004

[3] Krizhevsky, A., Sutskever, I., Hinton, G.E. (2012). ImageNet classification with deep convolutional neural networks. Communications of the ACM, 60, 84 - 90.

[4] Li Deng and Dong Yu "Deep Learning: methods and applications" by Microsoft research [Online] available at: http://research.microsoft.com/pubs/209355/NOW-Book-Revised Feb2014-online.pdf

[5] M. Zubair, J. Kim and C. Yoon, "An Automated ECG Beat Classification System Using Convolutional Neural Networks," 2016 6th International Conference on IT Convergence and Security (ICITCS), 2016, pp. 1-5, doi: 10.1109/ICITCS.2016.7740310.

[6] Rahime Ceylan, Yüksel Özbay, Bekir Karlik, 'A novel approach for classification of ECG arrhythmias: Type-2 fuzzy clustering neural network, Expert Systems with Applications', Volume 36, Issue 3, Part 2,2009, ISSN 0957-4174, doi:10.1016/j.eswa.2008.08.028.

[7] Li, Dan et al. "Classification of ECG signals based on 1D convolution neural network." 2017 IEEE 19th International Conference on e-Health Networking, Applications and Services (Healthcom) (2017): 1-6.

[8] Khan, Ali Haider; Hussain, Muzammil (2021), "ECG Images dataset of Cardiac Patients ", Mendeley Data, V2, doi: 10.17632/gwbz3fsgp8.2

[9] Letsas KP, Filippatos GS, Kounas SP, Efremidis M, Sideris A, Kardaras F. QT interval prolongation and Torsades de Pointes in a patient receiving zolpidem and amiodarone. Cardiology. 2006;105(3):146-7. doi: 10.1159/000091201. Epub 2006 Jan 4. PMID: 16449812.

[10] Hubel DH, Wiesel TN. Receptive fields and functional architecture of monkey striate cortex. J Physiol. 1968 Mar;195(1):215-43. doi: 10.1113/jphysiol.1968.sp008455. PMID: 4966457; PMCID: PMC1557912.
[11] O'Shea, Keiron Nash, Ryan. (2015). 'An Introduction to Convolutional Neural Networks' ArXiv e-prints, arXiv:1511.08458v2
[12] Deepika Jaswal, Sowmya.V, K.P.Soman, 'Image Classification Using Convolutional Neural Networks', International Journal of Advancements in Research Technology, Volume 3, Issue 6, June-2014 ISSN 2278-7763
[13] Grossi, Enzo Buscema, Massimo. (2008). Introduction to artificial neural networks. European journal of gastroenterology hepatology. 19. 1046-54. 10.1097/MEG.0b013e3282f198a0.
[14] Shukla, M. Abdelrahman, Mohamed. (2004). Artificial Neural Networks based steady state security analysis of power systems. 36. 266 - 269. 10.1109/SSST.2004.1295661.
[15] Ms. Sonali. B. Maind, Ms. Priyanka Wankar, 'Research Paper on Basic of Artificial Neural Network', International Journal on Recent and Innovation Trends in Computing and Communication, Volume: 2 Issue: 1, ISSN: 2321-8169