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Student Name: Prince Panjiyar

London Met ID: 19033703

College ID: np01cp4s200049

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I confirm that I understand my coursework needs to be submitted online via Google Classroom under the relevant module page before the deadline in order for my assignment to be accepted and marked. I am fully aware that late submissions will be treated as non-submission and a mark of zero will be awarded.

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Introduction:

For the working on the coursework, An AI topic has to be selected for the purpose of developing a system using AI algorithms. Here for this project, research on the AI domain problem with a proposed solution for it is needed. Pseudocode along with flowchart of the working proposed system is mandatory for this project. The topic that has been chosen to research on as the AI domain problem is Medical Imaging on ECG(Electro-Cardiogram) with CNN Algorithm.

A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning system that can take in an image, assign importance (learnable weights and biases) to distinct aspects/objects in the image, and distinguish one from the other. When compared to other classification methods, the amount of pre-processing required by a ConvNet is significantly less. While filters in primitive approaches are hand-engineered, ConvNets can learn these filters/characteristics with adequate training. Through the use of appropriate filters, a ConvNet may successfully capture the Spatial and Temporal relationships in a picture. Because of the reduced number of parameters involved and the reusability of weights, the architecture performs superior fitting to the picture dataset. In other words, the network may be trained to better recognize the image's sophistication. The ConvNet's purpose is to compress the images into a format that is easier to process while retaining elements that are crucial for obtaining a decent prediction (Saha, 2018).

An electrocardiogram (ECG) is a simple test that can be used to assess the rhythm and electrical activity of your heart. Sensors linked to your skin detect the electrical signals produced by your heart every time it beats. A machine records these signals, which a doctor examines to see if they are odd. An ECG is frequently used in conjunction with other tests to help diagnose and monitor heart problems. It can be used to look into signs of a cardiac disease, such as chest pain, palpitations (rapid heartbeats), dizziness, and shortness of breath.

Background:

Research and Problem Domain:

Artificial intelligence (AI) is a disruptive technology that use computerized algorithms to analyze complex data. Diagnostic imaging is one of the most potential clinical applications of AI, and increasing emphasis is being focused on establishing and fine-tuning its performance to assist identification and quantification of a wide range of clinical problems. Computer-aided diagnostics studies have demonstrated outstanding accuracy, sensitivity, and specificity for the identification of minor radiographic abnormalities, with the potential to enhance public health. However, in AI imaging research, outcome assessment is often characterized by lesion identification while neglecting the nature and biological aggressiveness of a lesion, which may result in a distorted picture of AI's performance.

The application of artificial intelligence (AI) in diagnostic medical imaging is being thoroughly researched. AI has demonstrated outstanding accuracy and sensitivity in the detection of imaging abnormalities, and it has the potential to improve tissue-based detection and characterization. However, with increased sensitivity comes a significant disadvantage: the identification of tiny changes of unclear importance. An investigation of screening mammography, for example, revealed that while artificial neural networks are no more accurate than radiologists in identifying cancer, they had consistently greater sensitivity for abnormal results, particularly small lesions. To guarantee successful and safe inclusion of AI-assisted diagnostic imaging into clinical practice, the medical community must anticipate possible unknowns of this technology at the start of an AI-assisted diagnostic imaging revolution (Ohad Oren, 2020). Machine learning, as a type of AI, sometimes known as classical AI, was first used in diagnostic imaging in the 1980s. Users initially set precise imaging parameters and characteristics based on professional knowledge. Shapes, areas, and histograms of picture pixels from regions of interest (i.e., tumor regions) can be retrieved, for example. Typically, for a given amount of accessible data items, a portion of them is utilized for training and the remainder for testing. To comprehend the features, a specific machine learning algorithm is used for training. Principal component analysis (PCA), support vector machines (SVM), convolutional neural networks (CNN), and other techniques are examples. The trained algorithm is then meant to detect the characteristics and categorize the picture for a specific testing image. In radiation therapy, it is frequently necessary to register one imaging modality to another (multimodal) or an image from one day to the next (monomodal). An unsupervised deep learning feature selection framework was presented to circumvent classical AI, which needed handmade features. To find inherent characteristics in picture patches, it used a convolutional stacked auto-encoder network. When compared to the state of the art, the algorithm produced higher Dice ratio scores. These techniques may be used for both multimodal and monomodal picture registration. Sloan et al. suggested a unique image registration approach based on regressing the transformation parameters with a convolutional neural network (CNN). This method was used in both monomodal and multimodal applications. With the encouraging results AI has showed in the research arena thus far (Tang, 2020). Some of the advantages of AI in the field of image diagnosis are:

- Provides real-time data addressing the medical issue saving the cost and patient wait time for the results.
- Streamlines Tasks as it helps health personnel to re-ensure their findings.
- Assists research
- Reduces Physicians Stress

With the various CNN-based deep neural networks constructed, we got a considerable result on ImageNet Challenger, the most significant picture classification and segmentation challenge in the image analyzing area. Deep neural systems based on CNN are commonly employed in medical categorization tasks. CNN is a powerful feature extractor, therefore using it to identify medical pictures can save time and money on feature engineering (Yadav, 2019). Convolutional Neural Networks include three sorts of layers:

- Convolutional Layer: Each input neuron in a conventional neural network is linked to the next hidden layer. Only a tiny portion of the neurons in the input layer link to the neurons in the hidden layer in CNN.

- Pooling Layer: The pooling layer is used to minimize the feature map's dimensionality. Inside the CNN's hidden layer, there will be several activation and pooling layers.
- Fully-Connected Layers: Fully Connected Layers are the network's final few layers. The output of the final Pooling or Convolutional Layer is flattened and sent into the fully connected layer as the input of the fully connected layer (Tripathi, 2021).

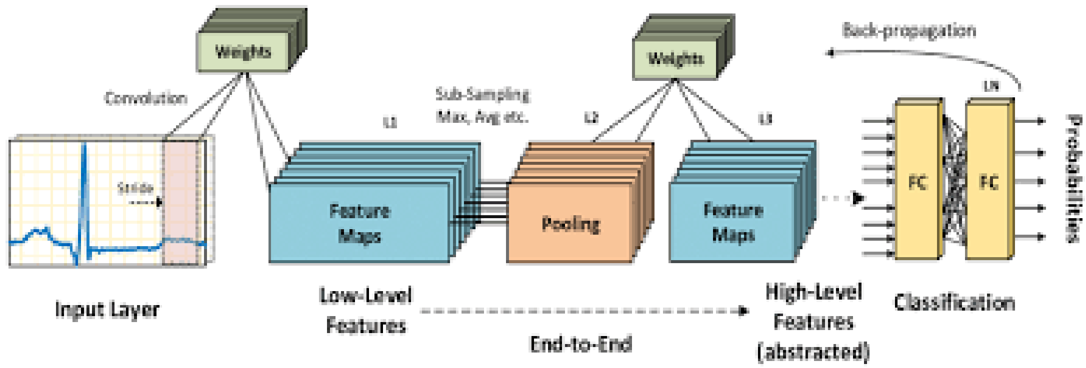

Figure 1 Working of CNN on ECG

Review and Analysis of Existing Works:

A Study on Arrhythmia via ECG Signal Classification Using the Convolutional Neural Network: By Mengze Wu, Yongdi Lu, Wenli Yang and Shen Yuong Wong

A one-dimensional 12-layer convolution neural network structure for classifying cardiac arrhythmia's five sub-classes CNN is a network that comprises of the following layers: input layer, convolution layer, pooling layer, fully-connected layer, and output layer. CNN, unlike standard neural networks, incorporates convolution and pooling layers that can extract and map features from input data to accelerate learning and decrease over-fitting. The two-dimensional convolution neural network has been widely employed in image processing because it possesses the multilayer perception property of the CNN. In this article, a one-dimensional 12-layer CNN is proposed to handle a one-dimensional time series with uniform interval sampling. Several changes are made to the network topology, such as using the suggested CNN network's average-pooling layer instead of the comparable CNN network's max-pooling layer. The average-pooling layer may keep the general characteristic of the input data, which is useful for classifying heartbeats. In comparison to the benchmark CNN network, the proposed CNN network features one extra alternating convolution and pooling layer. CNN network architecture suggested, with 8 alternating convolutions and average-pooling layers They are followed by two fully-connected layers and a dropout layer.

- Convolution Layer:

  This work employs a one-dimensional convolution kernel that convolutes independently of the feature map of the preceding layer to process a one-dimensional ECG signal. Offsetting the convolution kernel and passing it to the nonlinear activation function yields the convolution layer's output.

$$h_i^{l,k} = \mathrm{f}(b_i^{l,k} + \sum_{n=1}^{N} \mathrm{W}_{n,i}^{l,k} * \mathrm{x}_{i+n-1}^{l-1,k})$$

Where, $h_i^{l,k}$ is the output of the ith neuron in layer *l*, *f*() is the activation function and $b_i^{l,k}$ is the offset of the neuron in layer *l*. $x_{i+n-1}^{l-1,k}$ is the output of neuron in layer *l-1*, $W_{n,i}^{l,k}$ is the *k*th convolution kernels in *l*th layer.

- Pooling layer:

The pooling layer is generally formed by convolution of the following layer. By lowering the size of convolution layer output data, network complexity and overfitting are decreased. The network's robustness is improved as a result of this operation. The pooling layer averages or maximizes the convolutional layer's output features, and the associated algorithms are average pooling and maximum pooling.

- Fully-connected layer:

The fully-connected layer is used to increase the connection of all features after extracting features from various convolution layers and pooling layers. The SoftMax layer then does a logistic regression classification. The fully-connected layer sends the activation function the weighted sum of the preceding layer's output.

- Dropout layer:

Before the fully-connected layer, there is typically a dropout layer. During the training of the convolution neural network, the dropout layer will briefly detach certain neurons from the network based on a predetermined probability, which lowers joint adaptability between neuron nodes, minimizes overfitting, and improves the network's generalization ability.

The classification results of the proposed CNN network are displayed in the confusion matrix. The total classification accuracy rate of the five micro-class categorization of heartbeats is 97.41%, and the positive rate and specificity of each category are over 90%, demonstrating the model's usefulness (Wu & Lu, 2021).

ECG Signal Classification Using Deep Learning Techniques Based on the PTB-XL Dataset: By Sandra Smigiel, Krzysztof Palczynski and Damian Ledzinski

It is made up of five one-dimensional convolution layers with LeakyReLU activation functions and one fully linked layer with a SoftMax activation function. The network receives ECG data with 12 channels each containing 1000 samples as inputs and generates a class distribution vector normalized using the SoftMax function. By identifying the index of the vector maximum value, the network identifies the class to which an input signal belongs. The class represented by this index is regarded as an input signal class.

This architecture was evaluated on both the normalized signal from the dataset without any extra adjustments and a spectrogram, with the former yielding better results than the latter. Each spectrogram was interpreted as a multichannel one-dimensional signal by the network that computed it. Five one-dimensional convolutional blocks with the Leaky-ReLU activation function were used to analyze the spectrograms of the twelve signals. The convolutional results were pooled using adaptive average pooling. The pooling results were then flattened to a one-dimensional vector format and processed by a fully connected layer with a SoftMax activation function, with the output utilized as a vector expressing the probability distribution of the input signals belonging to each of the defined classes. This is a reduced architecture meant to improve computation speed as well as memory storage efficiency. This network includes just 6 layers and, depending on the number of classes in classification, only 8882 weights for binary classification and 11,957 weights for detecting 5 different signal classes. The network's last segment is a fully connected layer with a number of neurons equal to the number of different classes to which the signal might belong. As a result, the more detailed the classification process, the more neurons are required, increasing the total number of weights in the network. The inclusion of residual connections did not considerably improve network performance, but it did increase the number of parameters and computing steps necessary to analyze the signal. With the recognition of two classes, the network based on the convolutional network achieved 88.2% accuracy and with five classes 72.0% accuracy (Smigiel & Palczynski, 2021).

Proposed Solution:

Brief Explanation of the Approach:

For the purpose of better classifying the problem with least use of health personnel AI image detection through CNN is used. The CNN used has data set having 5 sets of Arrythmia sub-classes for the prediction of problem. The CNN uses 4 layers of Convolutional layer with Max Pooling of strides 2 using ‘ReLU’ as activation function. It uses flatten layer as to convert the data into 1-D array. It is finally connected to fully connected layer using “SoftMax” function for the final prediction.

AI Algorithm:

There are many AI algorithms for the classification of images like CNN, SincNet, CNN with Entropy Features, etc. Although the Convolutional Neural Network provides the best results with more accurate predictions on image classification. So, for this project CNN is used which is a type of Supervised Learning.

Supervised Learning:

A subset of machine learning and artificial intelligence is supervised machine learning. It is distinguished by the use of labeled datasets to train algorithms that properly categorize data or predict outcomes. As input data is fed into the model, the weights are adjusted until the model is well fitted, which occurs as part of the cross-validation process. A training set is used in supervised learning to educate models to produce the desired output. This training dataset contains both right and incorrect outputs, allowing the model to learn over time. The loss function is used by the algorithm to gauge its accuracy, and it adjusts until the error is suitably decreased (IBM, 2021).

Convolutional Neural Network:

A convolutional neural network (CNN/ConvNet) is a type of deep neural network that is often used to evaluate visual images in deep learning. When we think about neural networks, we usually think of matrix multiplications, but that is not the case with ConvNet. It employs a method known as Convolution. Convolution is a mathematical operation on two functions that yields a third function that explains how the form of one is affected by the other. Convolutional neural networks are made up of a number of layers of artificial neurons. Artificial neurons are mathematical functions that calculate the weighted sum of many inputs and output an activation value, which is an approximate replica of their biological counterparts. When you feed a picture into a ConvNet, each layer creates many activation functions, which are then passed on to the next layer.

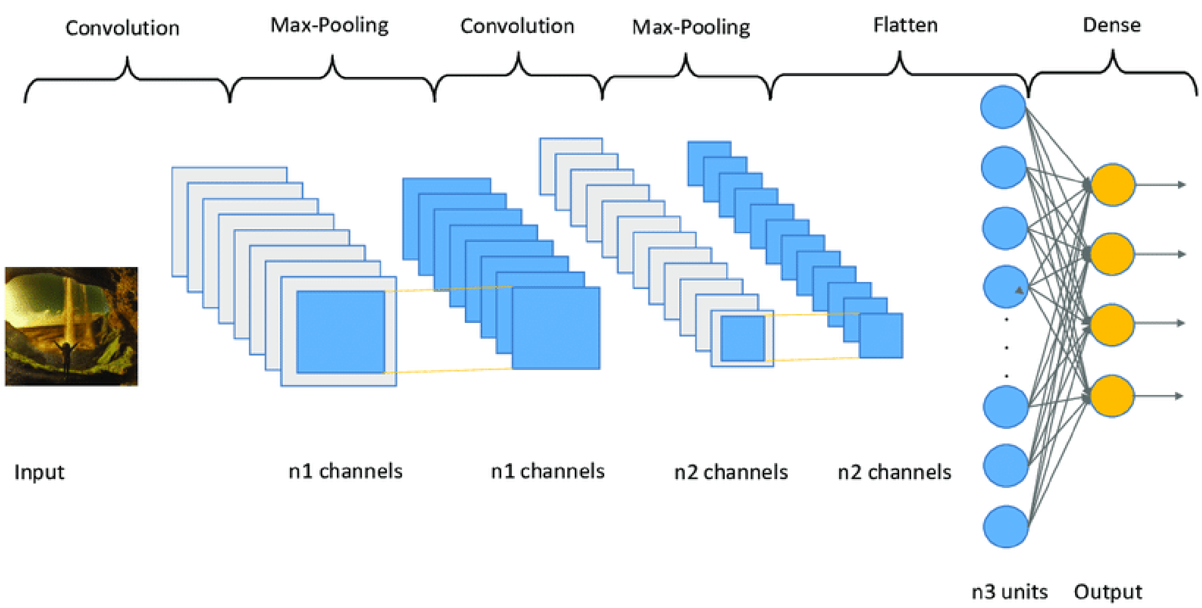

Figure 2 CNN Layers

Typically, the first layer removes fundamental information such as horizontal or diagonal edges. This output is sent to the next layer, which recognizes more complicated characteristics like corners or combinational edges. The Pooling layer is in charge of shrinking the spatial size of the Convolved Feature. By lowering the size, the computer power required to process the data is reduced (Mandal, 2021).

Pseudo-code:

Pseudo-code for CNN proposed model:

For i from 1 to 40 epoch do

For a from 1 to length of dataset do

‘a’ sent to 1-D conv layer for feature extraction.

Output to Max-pooling for maximizing features

The process repeats as layers of CNN and used 4 times.

Output from CNN layer sent to Flatten layer.

Output from above is sent to fully connected Dense layers of 12, 64, 32 perceptron with activation function of ReLU (Rectified Linear Unit)

Output from above is sent to Dense Layer of 5 perceptron with SoftMax activation function for the final output as prediction.

END for

END for

Diagrammatical Representation:

The Diagrammatical representation of proposed model is given below:

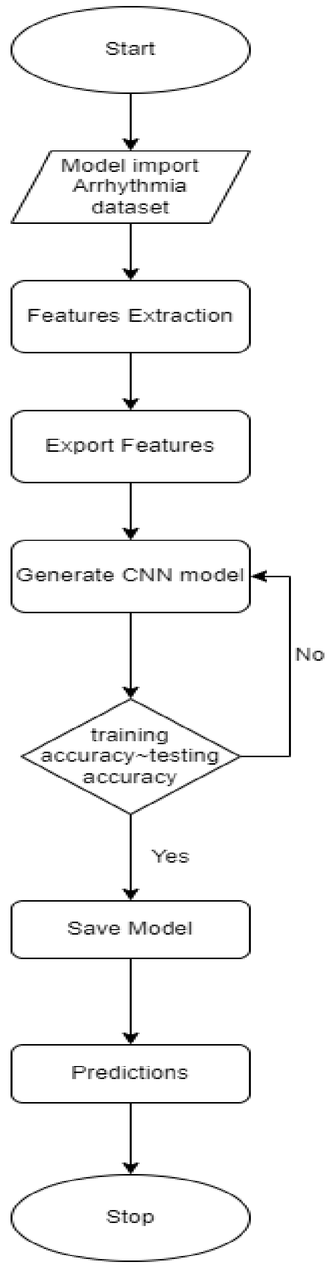

Figure 3 Flowchart of Proposed CNN model

Conclusion:

Analysis of work:

There are different works done for the proper image detection through different AI algorithms and models with different parameters. Many health centers use AI model for better classifying the diseases with in short period of time and using fewer human resources to manage cost. The model will help to enhance the classification of the diseases in the absence of well-trained health professionals and treat the patient accordingly without delaying in treatment of the patient.

Further Work:

As for the proposal for the creation of AI model for ECG prediction has been successfully created. The CNN algorithm and its various parameters used for the prediction system has been explained its implementation on the dataset to create more accurate model tuning the parameters and predicting the diseases with high accuracy is still to be developed.

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