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Coronary Artery Disease Diagnosis: A Deep Learning Approach for CAD Detection in CT Imaging

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Abstract: Heart disease is one of the leading global causes of death. Among them coronary artery disease contributing highest number of deaths it occurs when the main artery named coronary artery which supplies oxygen rich blood and many other nutrients to the heart gets thicker and narrower due to accumulation of fatty deposits a substance called atheroma is responsible for this. This is a very serious issue the world is currently and requires a proper cure. This paper studies on Computed tomography (CT) a heart diagnosis imaging technique which gives clear 3D image of any internal organ especially heart it checks the calcium, fat deposits in your arteries a deep learning techniques like convolutional neural networks (CNN), Visual Geometry Group - 16(VGG-16) which is typically a CNN model with deep layers, Visual Geometry Group - 19(VGG-19), Recurrent neural networks. The primary objective of this study is to create a highly accurate deep learning neural network model which takes images of CT scan by analysing the patterns in the image and tell us a person is having heart disease or not, This research made a comparative analysis of Both Machine learning models and deep learning models like Visual geometry group – 16(VGG-16) , Visual geometry group -19(VGG-19) and Recurrent Neural networks. It is observed that VGG-16 which is typically a CNN architecture has a performance similar to CNN Model, Whereas VGG-19 has showcased the best performance by giving highest accuracy and low false positive rate And Recurrent neural networks also performed well. This study is an example that deep learning models have better performance than ML models due to their ability to extract complex features.

Keywords: *CNN, Coronary Artery Disease, Deep Learning, Visual Geometry Group*

1. Introduction

Deep learning models play a significant role in identifying a person with heart disease or not it will consider many parameters like age, sex, blood pressure and match these patterns as these models are pre trained. One best thing about deep learning is it gives higher accuracy than traditional machine learning algorithms because of pattern observing nature and helps doctors in identifying disease so that doctors can take precautionary measures.

Convolutional Neural Networks (CNN) takes the CT images as the input and gets trained on them by analysing the complex patterns that's why it shows better accuracy than traditional machine learning algorithms. Fig. 1 shows the bar chart representation of the comparison of the Deep learning and Traditional Machine learning approaches.

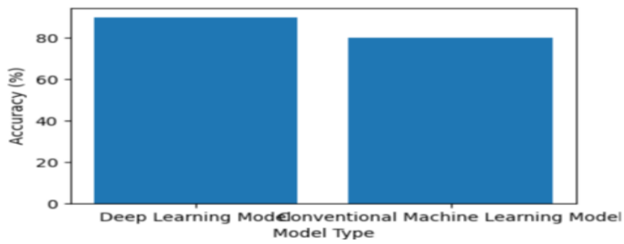

Fig. 1. Deep learning Vs Traditional Machine learning. Compared to machine learning algorithms deep learning have significant impact due to its ability to extract complex features

Computed tomography scans person around him/her completely which takes 3D images of heart, arteries to see whether there is a blockage, narrowing of arteries, pumping level of blood, percentage of blockage into account.

The symptoms of this disease majorly include.

- High blood pressure: people with high BP tend to get a chance of heart attack as the blood vessels get damaged due to High bp.

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- May experience shoulder pain and often has trouble in breathing.
- Difficulty in climbing high staircase.
- shortness of breathing can be caused by many reasons but one such is due to left ventricle don't supply enough blood, so the task needs to be accomplished by right ventricle itself.
- A rare condition where people may experience diarrhoea also.

Authors in Eriksson et al. (2001) identified challenges in identifying early stage Heart disease To overcome that they Performed longitudinal study on Men From birth to adult By considering Ponderal index (PI) which is ratio of mass per height and large sample size data observed that people who are less than one year and experiencing a slower weight gain tend to have higher chance of getting heart disease, After finishing the infant period people who are gaining weight vastly tend to get heart related issues, The study also found that people who are obese during their childhood may face heart related issues in future so during initial period of childhood must be taken care of. This study conducted by Eriksson is far better than existing approaches as these studies mostly cross-sectional, Which means they considered only a short amount time which may not be sufficient. Moreover, the study used a large sample size, which made the results more reliable.

Authors in Lee et al. (2019) Observed that identifying lipid content and fat accumulation in arteries is difficult task with traditional methods like ultrasound. However, By using Computational fluid dynamics (CFD) a branch of fluid mechanics that solves problems involving fluid flows, In CFD they stimulated blood flow to the heart and identified the areas where there is low blood flow which are typically plaque accumulated. CFD provides strong evidence by giving higher accuracy and identifying very minute plaque deposits.

There is Non-calcified plaque in which no calcium traces is not found as we seen in calcified plaque, Due to this identifying Non-calcified plaque is difficult through X-Rays and it requires CT to identify them. Especially people with smoking habits which will damage the blood vessels have higher tendency to Form this type of plaque. Fig. 2 shows the difference between calcified and noncalcified plaque.

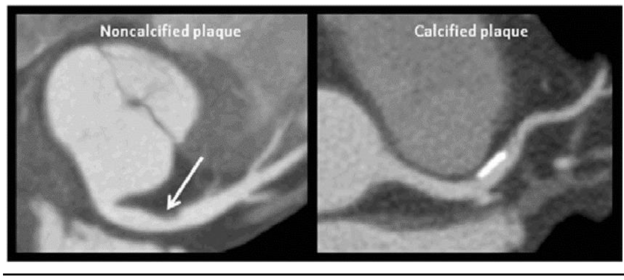

Fig. 2. Noncalcified plaque Vs Calcified Plaque taken by Computed tomography scan of arteries. Left artery showing traces of Noncalcified plaque and Right-side showing Plaque deposits which contains calcium.

Authors in Evangelos et al. (2019) Idnetified drawbacks in Computed tomography scans and it is observed that Traditional risk factors like age, gender and so on.. Don't give exact idea of a person's heart condition as many of the initial model considered them. However they identified fat attenuation index (FAI) which measures the amount of fat deposits around coronary arteries and plays a key factor in identifying the people with CAD.

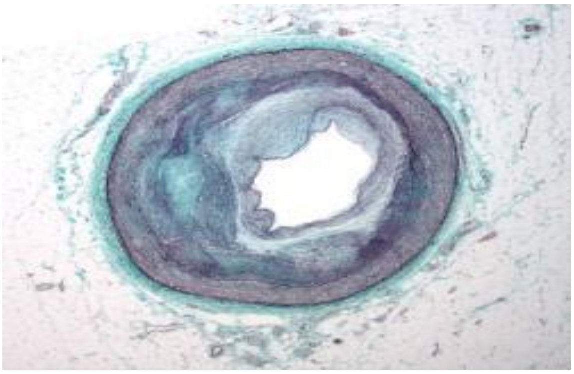

Fig. 3. Plaque Accumulation in artery taken by Magnetic Resonance Imaging(MRI) shows Narrowing of arteries due to plaque accumulation a fatty substance which consists of proteins, lipids.

Authors in Rine Nakanishi et al. (2019) Identified potential challenges in identifying atherosclerosis (disease occurs when plaque accumulated in arteries which supplies blood to the heart), with traditional methods like ultrasound and stress testing. However, this drawback can be overcome by Coronary computed tomography angiography especially when the blockage is > 50%, This is due to its ability to extract complex features.

Authors in Shan et al. (2020) identified that there is association with food intake and risk of heart disease because a study conducted by them found that the diet which people intake has a tremendous impact on telling whether a person getting cardiovascular diseases or not, people who consume Mediterranean diet which mainly includes plants, fruits and vegetables tend to have lower chance of getting Heart related diseases. This particular eating pattern is subjected to gender, and the age of person.

2. Literature Work

Authors in Duncan et al. (2019) conducted a survey on individuals who have quitted smoking and identified that the risk of getting Heart disease is lowering as the time passes by, People who avoid smoking technically referred as Smoking cessation have reduced the percentage of getting Cardiovascular diseases, also mentioned that the risk is still high when compared to people who didn't smoke at all in their life. Also there are numerous amount of benefits like improving sleep quality, enhanced blood circulation and better sleep quality by assuring overall health of the person.

Authors in Debras et al. (2022) conducted a survey on individuals who intake artificial sweeteners for a period of 7.7 years and found that Cardiovascular risk is high among them than the people who don't consume them. Women may have higher risk of CVD than men in people consuming artificial sweeteners This may be due to hormonal changes and lifestyle habits. So according to them the risk associated with Artificial sweeteners and heart related diseases is very high.

Authors in Ohkuma et al. (2019) Provided a strong evidence by performing observational studies on individuals and found that people who are associated with diabetes have 2.2 fold chance than any normal individual this is due to the variation in blood pressure and cholesterol levels, however it is quite higher in women having diabetes especially people with type -1 diabetes(a condition in which body destroys its cells).

Authors in Rodgers et al. (2019) used existing research and provided an overview on Cardiovascular diseases and their impact with ageing, Also the author identified by making statistical analysis that men have higher chance of getting CVD at an young age than women but the research showed that women have higher chance to die. But the impact can be reduced by following some preventive measures by having nutritious diet, having regular exercise and avoiding heavy lifting tasks.

Authors in Han & Liu. (2020) utilised the concept of deep learning to build a model which takes the Computed tomography images of patients with heart issues because their ability to analyse complex patterns during training data, these images are assigned with numerical value which indicates how severe it is then 80% of the data is used for training and the rest 20% for validation data. Author used area under the curve (AUC) to analyse the performance and AUC of 0.978 is achieved which means around 97% cases the deep learning model is predicting accurately.

Authors in Daniele Andreini et al. (2019) Proposed to use Fractional flow reserve in diagnosing people with Multivessel Coronary Artery Disease(at least 2 or more arteries were blocked or narrowed). Author considered distal -blood pressure where part of artery moving along with downstream part, pressure proximal- indicates upstream of the artery by considering these both produced promising results with an accuracy of 98%. by giving best decision making in heart treatment and outperforming standard methods like angiography techniques.

Authors in Lukas D et al. (2022) Made a comparative analysis of Coronary computed tomography angiography(CCTA) and Cardiac magnetic resonance(CMR) by comparing its risks like CCTA is more prone to ionizing radiation exposure but CMR don't. Moreover, apart from all these CCTA is highly accurate and economically affordable and concluded that CT is much more better due to its large availability.

Authors in Wei wu et al. (2020) utilised the concept of deep learning to build a CNN model called deconvolutional neural network that is well-suited for object detection tasks. Author considered X-ray images of patients with coronary heart disease, and they fed as an input to model which is initialised with random weights then the CNN model gives probability as an output which indicates the presence of plaque deposits. Finally, loss function is computed to adjust the weights and make the model sparser.

Author in Amit arbune et al. (2021) conducted a tilt table test which is done on a person, when a person stands the blood pressure should drop but in this case it Blood pressure is raising this is an indication that the m person may have heart related issues since the raising blood pressure indicates that there is constriction of blood vessels. The author referred this condition as Pheochromocytoma is a condition that develops tumours which results in high blood pressure and anxiety issues.

Authors in Roman Z et al. (2021) investigated the existing challenges in identifying a person with heart disease, so to overcome that proposed a Convolutional neural network, which is trained on data and this knowledge is used to localizing the arteries, This is important because it yields high accuracy and predicts the probability of each pixel which finally produced segmented image of heart. This method outperformed existing methods in terms of accuracy around 90 percent.

Authors in Marly van et al. (2021) utilised the concept of deep learning to build a Deep neural network using CNN to identify calcium deposits, Initially Author pre-processed the images and normalized them, thereafter the model is trained on a large amount of Chest CT scans and the model performed well on testing data by identifying Calcium deposits from the images. Novelty is author used Agatston score and got an accuracy of 92 percent which tells 92 percent of the cases model detected calcium from the images.

Authors in discharge trial group et al. (2022) used existing research and made comparative study that says Initial Ct - Scans which are performed before any diagnostic tests is better than initial ICA because of the risks associated with it since ICA is prone to heavy bleeding and it is less safe, more expensive. So it is advisable to go with CT scan for both men and women who are suffering with chest pain and symptoms which are associated with heart.

Authors in David et al. (2022) conducted a literature survey which says that Computed tomography is useful in diagnosing patients with coronary heart disease because it helps to identify people with CAD by analysing risk factors and if the risk is high enough it suggests some vigorous practises for the patients to reduce the impact off the disease to some extent. However, there are some limitations and it need to be improved.

Authors in Alasdiar et al. (2021) conducted a controlled medical trial in which a contrast dye is injected into patients' vein to observe internal organs of the body more clearly. Also mentioned that It also lowers the risk of Unplanned revascularization by improving the blood flow to the heart muscle.

Authors in Hiroki Kobayashi et al. (2020) Proposed a CNN model where the models purpose is to improve low resolution images taken through Magnetic resonance imaging(MRA).At first Author trained on both high and low resolution images so that model extracts features from it and when new image is given it makes comparison accordingly and improve quality of low resolution images as well, Finally the converted image is refined to make less prone to errors.

3. Methodology

The process of CAD detection using a convolutional neural network (CNN), as illustrated in Figure 4, begins with resizing the input image for efficiency. Subsequently, data preprocessing normalizes pixel values and converts the image to a specific colour space suitable for the CNN. The CNN comprises convolutional layers that learn to extract image features through filter application, followed by pooling layers to reduce feature map dimensionality while preserving crucial information via max pooling. Fully connected layers then combine this feature maps into a single feature vector, enabling image classification based on extracted features. The output layer yields a probability representing CAD presence in the image. The CNN is trained on labeled CAD or non-CAD images, learning to associate image features with CAD presence. This trained model can effectively detect CAD in new images, and while the depicted CNN model is relatively simple, more complex models exist for improved performance, necessitating larger datasets and computational resources.

3.1. Dataset Overview:

The dataset consists of training, validation Computed tomography images of patients who are tested positive and negative for coronary heart disease. Fig. 4 shows the proposed architecture.

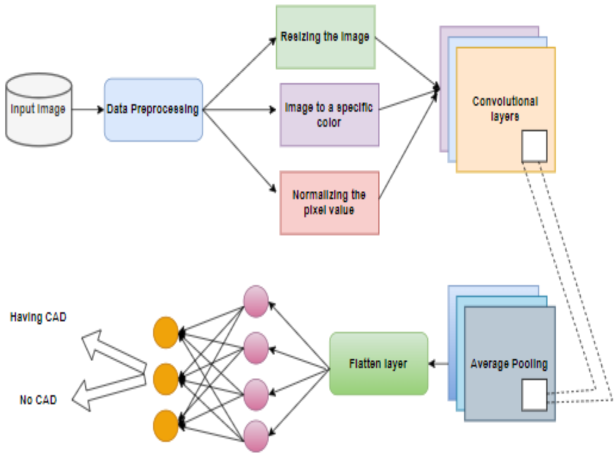

Fig. 4. Architecture of the Model shows the algorithm flow

In the below Fig. 5 shows the representation of each layer and its type, also including the models architecture, Number of trainable parameters.

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 148, 148, 32)	896
max_pooling2d (MaxPooling2D)	(None, 74, 74, 32)	0
conv2d_1 (Conv2D)	(None, 72, 72, 64)	18496
max_pooling2d_1 (MaxPooling2D)	(None, 36, 36, 64)	0
conv2d_2 (Conv2D)	(None, 34, 34, 128)	73856
max_pooling2d_2 (MaxPooling2D)	(None, 17, 17, 128)	0
conv2d_3 (Conv2D)	(None, 15, 15, 128)	147584
max_pooling2d_3 (MaxPooling2D)	(None, 7, 7, 128)	0
flatten (Flatten)	(None, 6272)	0
dense (Dense)	(None, 512)	3211776
dropout (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 1)	513

Fig. 5. Summary of models Architecture representing different layers of the model like convolutional and maxpooling layer and the number of trainable parameters at each layer.

3.2. Data Preprocessing: Data Preprocessing is done to ensure it is error free as part of it Data augmentation techniques like resizing, rotation, shearing, normalizing the pixels is done.

3.2.1 Resizing Image: Resizing image helps to capture all the important features so that it helps to make a better classification.

3.2.2 Normalizing the pixel value: It ensures every pixel in the image have some specific range because higher pixel values become more complicated so in order to avoid that they are divided by some specified value to take them to 0 – 1 range.

Equation for normalizing the pixel values in an image:

$$normalized_{pixel_{value}} = \frac{(pixel_{value} - minimum_{value})}{(maximum_{value} - minimum_{value})} \quad (1)$$

3.3. Support Vector Machines:

SVM Which stands for Support Vector Machines is a supervised machine learning technique means that the data is labelled which indicates the model is fed both inputs and expected output the model need to identify the underlying pattern in the data. It can be used for both classification and regression tasks as well, the purpose is to find a optimal hyperplane that maximizes the distance between the points which are referred as support vectors which are nothing but data points that are being classified.

3.4. Logistic Regression:

It is also a supervised machine learning technique in which it predicts whether a thing belongs to a particular class or not, Logistic regression works by taking input data which consists of a greater number of features. For example, consider if the goal is to predict whether tomorrow will rain or not this depends on many factors like temperature, climate these acts as features. Then a logistic regression calculates weighted sum of these features, Since the output is in terms of probability Sigmoid activation function is used to normalize these values to 0-1 range.

3.5. Decision Trees:

The main goal of a supervised machine learning approach widely used for classification purposes is to query the root node and create a tree-like structure It creates a flowchart-like tree structure in which each node represents a trial feature so, each branch test result, and each leaf node (terminal node). Stopped-requirements, according to the values of the features, are obtained by iteratively decomposing the training data into subsets.

3.6. Convolutional Neural Networks:

CNN it’s a deep learning technique especially useful for image classification techniques. It is vey helpful in coronary heart disease detection using computed tomography. It takes CT images of heart as an input and then the images undergo convolutional operation to extract important features Followed by feature sampling is done the sampled features is given to a fully connected layer before finally classifying the image.

3.7. VGG16 and VGG19:

VGG16 and VGG19 are deep convolutional neural networks developed by the Visual Geometry Group (VGG) at the University of Oxford. These models are famous for their simplicity and effectiveness in image classification tasks.

3.7.1 VGG16:

VGG16 consists of 16 layers, including 13 convolutional layers and 3 fully connected layers. It uses 3x3 convolutional filters with a small stride, followed by max-pooling layers. The architecture is characterized by its deep stack of layers, which allows it to learn hierarchical features from images. VGG16 is widely used as a feature extractor in various computer vision applications and can achieve high accuracy in image classification tasks.

3.7.2 VGG19:

VGG19 is an extension of VGG16, with 19 layers in total. It maintains the same architecture but with more convolutional layers. The additional layers can capture more complex patterns in the data but also make the model computationally more intensive. VGG19 is useful when finer-grained feature extraction is required, but it may be slower and requires more resources compared to VGG16.

3.8. Recurrent Neural Networks (RNNs):

RNNs are a class of neural networks specifically designed for sequence data, such as time series data, natural language, and audio. Unlike CNNs, which excel at processing grid-like data like images, RNNs are designed to work with sequential data, where the order of elements matters. RNNs have recurrent connections that allow them to maintain a hidden state that can capture information from pervious time steps. This makes them suitable for tasks like time series prediction and natural language processing.

3.9 Regularization:

Regularization is associated with some techniques that are preventing overfitting, it occurs when the model is heavily and performs poor and give bad accuracy on testing data i.e., Model It works fine when using training data but not when using testing or raw data. This happens because the model is not learning underlying trend in the data. However, there are some techniques to prevent overfitting, Regularization works by adding a penalizing term which discourages to learn highly from training data thereby minimizing the loss function. Below mentioned are some of the Regularization techniques which are commonly used in deep learning models.

3.9.1 Underfitting:

Underfitting occurs when the model is not able to perform on training data as well so as a result on testing data it doesn't perform. It occurs due to high bias.

Bias: Refers to the error which occurs when we are trying to fit real world data into the model in which we are trying to fit. This happens when the model is oversimplified and fails to detect a hidden pattern in the data.

.The below “Fig. 6” showing how the data is distributed in high biased and High variance model.

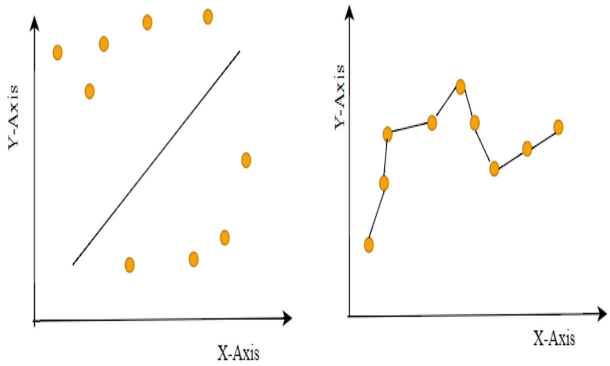

Fig. 6. High bias Vs High variance, High bias in the left side is due to difference in models prediction verses its target value and right pic shows High variance which results in overfitting.

3.9.2 L1 Regularization:

Aka Lasso regression in which weights are taken as absolute magnitude because there is a need to penalize them irrespective of no matter how good or bad. The Eq 2 represents a regularized cost function that represents the lasso regression J(θ) used in machine learning, where hθ(x) is the predicted output, y is the actual output, and λ is a regularization parameter λ∑_{j = 1}^n |θj| penalizes large parameter values.

$$J(\theta) = \text{Cost}(h\theta(x), y) + \lambda \sum_{\{j=1\}}^{n} |\theta j| \quad (2)$$

3.9.3 L2 Regularization:

Aka Ridge regression in which squared magnitude is added as penalty term to penalize the loss function. The equation represents a regularized linear regression cost function (J) consisting of mean squared error (MSE) and a penalty term λ/2 ∑_{j = 1}^n θj^2 to prevent overfitting.

$$J(\theta) = \text{MSE}(\theta) + \frac{\lambda}{2} \sum_{\{j=1\}}^{n} \theta j^2 \qquad (3)$$

In Fig. 7, the blue line represents L1 Regularization as the Regularization strength(λ) increases the absolute values of coefficients also increases, this is because to make the data sparse by making unimportant features to zero. Whereas in L2 Regularization instead of making it to zero the coefficients are reduced to maximum possible extent.

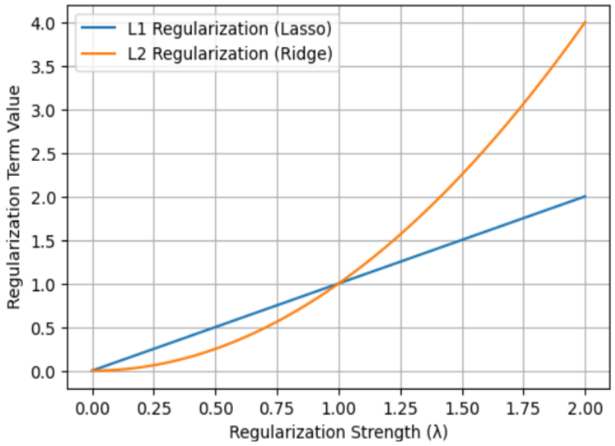

Fig.7. L1 vs L2 Regularization, Blue line represents L1 regularization which is making coefficients to zero where as in L2 regularization orange line The coefficients are reduced to maximum extent without making it to zero.

3.9.4 Dropout:

Dropout refers to dropping off some nodes at every iteration, it’s a technique which is implemented in neural networks to avoid overfitting problem. Generally, a model undergoes overfitting when the has good performance on training data but not on test data. As a result, it leads to false predictions, so to avoid that Dropout remove nodes with a dropout probability 'P’, as a result the model will be generalised and works well on unseen data. Below “Fig. 8”is the pictorial representation of before and after applying dropout.

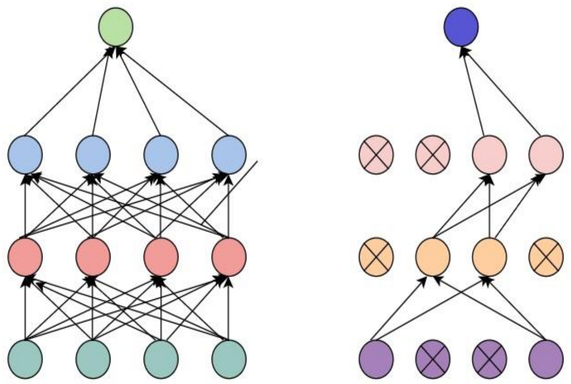

Fig.8. Before and After applying Dropout

$$\textit{Formulae}: \text{output} = \text{input} * (1 - \text{dropout}_{\text{rate}}) \ (4)$$

3.9.5 Early Stopping:

It is also one of the techniques to avoid overfitting, Early Stooping is mainly used to reach a convergence point in which the model needs to be stopped after achieving a certain defined accuracy without getting overfit. So in order to happen the training epoch need to be stopped by using callback function which stops model training after certain number of epochs.

3.9.6 Algorithm:

Input: Set of images M having labels N

Output: Need to Build a Convolutional Neuron model say P.

Set the weights for the CNN model randomly.

For every epoch:

The dataset should be divided into training and validation sets.

Then train the CNN model P on the specified dataset Then follow below steps:

i)Forward Pass: It calculates Output for the given input image.

ii) Evaluate Loss: Actual Value - Predicted Value.

iii) Backward Pass: Reconstruction of the input layer by adjusting the parameters.

Now Evaluating the model on validation data by using below steps:

i)Performance Evaluation: Check the output for the given input image.

ii)Accuracy Check: Assess the performance by calculating the total percentage of images predicted correctly.

Terminate training when there is no improve in validation accuracy. Now predicting labels:

1. Loading the image form a specified directory path:

img = image.load_img(image_path, target_size=(150, 150))

2. Converting the image into array for representing data:

   img_array = image.img_to_array(img)

3. Add batch dimension of size 1 to the array:

   img_array = np.expand_dims(img_array, axis=0)

4. Normalize the image - Scale it to similar range:

   img_array /= 255.0

5. Make a prediction:

   prediction = M(img_array)\

6. Determine the predicted label:

predicted_label = "Positive CHD" if prediction [0] > 0.5 else "Negative CHD"

Below is the step wise implementation for the above algorithm:

Step 1: Importing the libraries: First we need to import the necessary libraries required and by providing directory path in which the images resided.

Step 2: Data Preprocessing: Before preprocessing images are resized so the trained model able to capture features like plaque in a clear way then as part of preprocessing data augmentation techniques like, rescaling, rotation, shear, is done to ensure the trained model perform efficiently.

There after it undergoes pooling to create a feature map the below "Fig. 9" show sampling operation

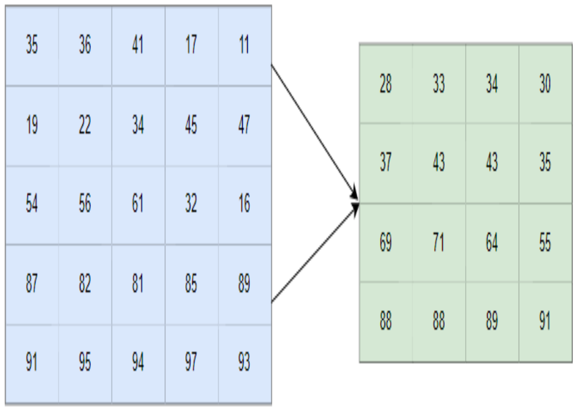

Fig. 9. Feature extraction using max pooling as a result number of features are reduced to make sure dimensionality reduction takes place, So that unimportant features were removed.

The equation for average pooling in CNN is:

$$Feature_{map} = \frac{\sum_{i=0}^{Pooling\_size-1} \sum_{j=0}^{Pooling\_size-1} Input\_image_{i,j} \cdot Kernel_{i,j}}{\left(Pooling\_size\right)^2} \quad (5)$$

Step 3: splitting the data: The data is then divided into train_generator which consists batches of image for training purpose and the validation_generator is for accessing the performance of the model.

Step 4: Defining the model: A sequential CNN model is defined where the input image undergoes convolutional layer then a feature map is created by Max-pooling. After dense layer is created to prevent overfitting, 0.5% dropout rate is specified.

Step 5: Training the model: Model is trained on the image dataset consisting of the images of heart disease patients.

Step 6: Testing the model: The model is then tested on the images by loading them and got an Test accuracy of 93.2%.

Step 7: Making Predictions: The image is predicted and its classified as Positive CHD and Negative CHD.

4. Experimental Setup

This work requires windows 10 and python 3.8 version with libraries like TensorFlow, NumPy which is helpful for matrix operations and helps in data preprocessing, matplotlib for visualizations, keras which helps to build and define the model. For our research on coronary heart disease using CNN, we have taken Computed tomography images of various patients to make risk prediction and predict whether they are positive or negative to CAD.

5. Results and Discussions

This study considered Computed Tomography dataset of patients who are having coronary artery disease and negative to CAD, Various data augmentation techniques like rescaling, rotation, shear were done to make the model much more generalised so that it can be able to predict unseen images. CNN model is created by having polling, flatten and dense layers for the image needs to be undergo and then dropout is applied to avoid the problem of overfitting. Since initially division images into batches and applying Adam optimiser which is a optimisation technique that can updated the learning rate by considering series of past gradients, As a result This added a valuable insight and improved our work by innovating it.

Implementing the techniques results obtained are, SVM got an accuracy of 81.06%. Logistic regression achieved 84.6. Decision Tree achieves around 83.2%. Finally Convolutional neural networks achieved highest accuracy of 87.1, The below “Fig. 10” shows analysis of the model’s performance in various aspects.

	SVM	Logistic Regression	Decesion Treee	Convolutional Neural Networks	VGG -16	VGG- 19	RNN
Accuracy	81.06	84.6	83.2	93.2	92	96	94
Precision	96.56	96.56	96.5	96.83	96.47	99	96.84
Recall	82.81	86.67	85.14	95.54	95.08	96.9	96.3
F1-Score	89.16	91.35	90.5	96.18	95.77	97.87	96.8

Fig 10. Performance Evaluation of Various Models

The below “Fig. 11” represents classification of CT images which are obtained

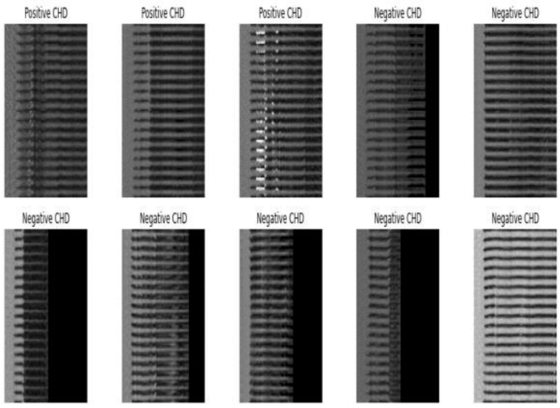

Fig 11. Classification Of CT Images

6. Conclusion

From the results obtained CNN achieved an highest accuracy of around 87.1% compared to other machine learning models and they are as follows SVM (81.06%), Logistic Regression (84.6%), Decision Tree (83.2%), CNN(93.2%).The order is as follows CNN>Logistic Regression>Decision Tree>SVM

The accuracy for convolutional neural networks is highest because their ability to extract features from the images and since data augmentation is done the model is trained on images of different size, contrast, brightness and angle so that any unseen image is given it can able to predict without any false possibility. Also, overfitting techniques like dropout are implemented which turned off neurons with a defined probability of p = 0.5 in order to avoid complexity of the model as a result model will be generalised and can make better predictions on new data as well.

7. Future Scope

To make this work into a real-world application by taking users data Using API which takes persons medical parameters like CT images which consists of arteries, Blockage of blood vessels and plaque deposits and our corresponding deep learning algorithm will give accurate results.

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