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CNN ALGORITHM FOR BREAST CANCER DETECTION OF MAMMOGRAM IMAGES

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ABSTRACT:
The accurate detection of breast cancer plays a vital role in improving patient outcomes and reducing mortality rates. To address this critical need, a Deep Learning technique based on Convolutional Neural Networks (CNNs) was proposed to enhance the predictive model for breast cancer identification. This model focuses on classifying mammogram images as either benign or malignant. The study utilized a diverse dataset of mammogram images, encompassing various cases, which were partitioned for training, validation, and testing purposes. The CNN architecture was employed to construct the predictive model, leveraging its ability to learn intricate patterns and features indicative of breast cancer. The implementation of advanced machine learning models for breast cancer detection contributes to the medical field's ability to deliver precise diagnoses and improve patient outcomes. By leveraging the capabilities of CNNs, this model aids in the early detection of breast cancer, potentially saving lives and positively impacting individuals affected by the disease.
Keywords: CNN, mammogram, benign, malignant , Artificial Intelligence, Deep Learning

1.Introduction:

The detection and assessment of breast cancer are crucial for ensuring early diagnosis, effective treatment, and improved patient outcomes. Traditional methods have been surpassed by innovative approaches that leverage advanced technologies, including Artificial Intelligence (AI). By accurately analyzing mammogram images and extracting meaningful information, AI-based methods enhance decision-making throughout the breast cancer detection process.
The assessment of breast cancer using AI involves the application of machine learning algorithms and image processing techniques to analyze mammogram images. These methods aim to develop robust and efficient models for breast cancer detection and classification. One of the major challenges in breast cancer detection is the accurate identification of malignant tumors amidst healthy breast tissue. This task traditionally relied on manual interpretation, which was time-consuming, prone to human error, and less efficient. Additionally, manual classification increased the risk of missed diagnoses or unnecessary interventions. By implementing AI-based systems, these challenges can be addressed, reducing the burden on healthcare professionals, improving accuracy, and optimizing patient care[1,2].

Ongoing efforts in breast cancer detection aim to address various challenges, including the variability of breast tissue, environmental factors that can affect the appearance of tumors, and the need for models that can handle multiple types of breast cancer simultaneously. By developing robust AI models, researchers and clinicians strive to improve sensitivity and specificity in breast cancer detection, ultimately leading to earlier diagnoses, better treatment planning, and improved patient outcomes.

The benefits of AI-based breast cancer detection are significant. By ensuring early and accurate detection, these methods can aid in reducing mortality rates and improving survival rates for breast cancer patients. Additionally, AI-driven models can assist healthcare providers in making informed decisions regarding treatment options, leading to personalized and targeted therapies. Furthermore, AI-based detection systems have the potential to streamline the detection process, reducing wait times, healthcare costs, and patient anxiety.

In conclusion, the application of AI and advanced technologies in breast cancer detection holds immense potential for improving patient outcomes and optimizing healthcare processes. By automating and enhancing the detection and assessment of breast cancer, AI systems reduce reliance on manual interpretation, improve accuracy, and aid in timely interventions. Ongoing research and development efforts in AI-driven breast cancer detection are critical for meeting the demands of patients, healthcare providers, and society as a whole, as they contribute to early diagnosis, effective treatment, and ultimately, the fight against breast cancer.

2. Methodology:

Deep neural networks, particularly convolutional neural networks (CNNs), have been demonstrated to be good at recognizing image patterns[3,4]. The Primary Objective of Assessment of health of fruits using AI is to develop efficient methods for classifying the fruits. We used CNN model for analyzing our data for assessment of health of fruits

Convolutional Neural Network (CNN):

The CNN architecture comprises several fundamental components.

2.1 Convolutional layers:

The convolutional layer is responsible for extracting features from input images in a convolutional neural network (CNN). It performs the mathematical operation of convolution by sliding a filter of size MxM over the input image. The filter calculates the dot product between itself and the corresponding parts of the input image, capturing local patterns and features. This process allows the network to learn and detect important visual patterns, such as edges, textures, and shapes, which are crucial for higher-level image understanding and classification tasks.

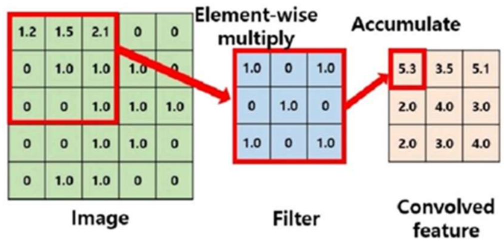

Fig 1: Convolution Operation

The output of the convolutional layer in a CNN is known as the feature map, which provides information about the image, including corners and edges[3]. This feature map is then passed on to subsequent layers to learn additional features of the input image. The convolutional layers in CNNs are advantageous because they preserve the spatial relationship between pixels, allowing the network to capture local patterns and spatial dependencies. This property enables CNNs to effectively learn and represent complex visual information in images[5].

2.2 Pooling layers:

In convolutional neural networks (CNNs), the Convolutional Layer is often followed by a Pooling Layer. The main purpose of the Pooling Layer is to reduce the size of the convolved feature map, thereby reducing computational costs and controlling overfitting[6,7].

The Pooling Layer operates independently on each feature map and decreases the spatial dimensions. By doing so, it reduces the number of connections between layers and compresses the information from the previous layer. This compression helps in summarizing the features generated by the Convolutional Layer.

There are different types of pooling operations that can be applied, including Max Pooling, Average Pooling, and Sum Pooling. In Max Pooling, the largest element within each predefined section of the feature map is selected[7,8]. This retains the most prominent feature in that section. Average Pooling calculates the average of the elements within each predefined section, providing a general representation of the features. Sum Pooling computes the total sum of the elements within each predefined section, capturing the cumulative strength of the features.

The Pooling Layer acts as a bridge between the Convolutional Layer and the Fully Connected (FC) Layer. It reduces the spatial dimensions while retaining important features, enabling the FC Layer to work with a more compact representation of the input. This helps in reducing the computational requirements and improving the efficiency of the network.

Overall, the Pooling Layer plays a crucial role in CNN architectures by summarizing the features obtained from the Convolutional Layer, reducing spatial dimensions, and aiding in computational efficiency and control of overfitting. The choice of pooling operation depends on the specific requirements of the task at hand and the desired properties of the extracted features.

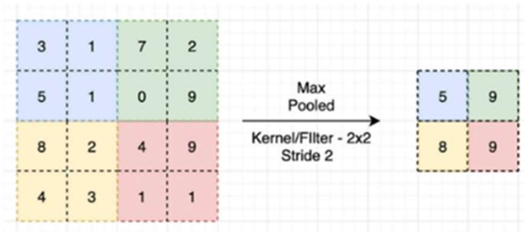

Fig2: Pooling Layer

This CNN model generalises the features extracted by the convolution layer, and helps the networks to recognise the features independently. With the help of this, the computations are also reduced in a network.

2.3 Activation function:

In convolutional neural networks (CNNs), activation functions play a crucial role in introducing non-linearity to the network's outputs. They determine whether a neuron should be activated based on the input it receives. Activation functions enable CNN models to learn and predict complex patterns by performing mathematical operations on the inputs. By applying non-linear transformations, activation functions allow the network to capture and represent intricate relationships in the data. This non-linearity is essential for CNNs to effectively handle tasks like image recognition, object detection, and semantic segmentation, where the underlying patterns are often nonlinear in nature.

2.4 Fully connected layers:

Fully connected layers combine learned features and make predictions. Neurons in these layers are connected to every neuron in the previous layer.

The FC layer consists of weights, biases, and neurons. Its primary function is to take the output from the previous layers and flatten it into a vector. This vector is then passed through the FC layer, where mathematical operations and transformations occur[5]. The FC layer serves as a bridge between the convolutional and pooling layers and the final output layer.

The purpose of using multiple FC layers is to improve the performance and accuracy of the classification process[9]. By connecting multiple FC layers, the network can learn more complex representations and extract higher-level features from the input data. Each FC layer performs its own set of mathematical operations, allowing the network to capture more intricate patterns and relationships within the data.2.5 Softmax function:

The softmax layer is often the final layer in classification tasks, producing class probabilities by normalizing previous layer outputs into a probability distribution across classes[10].

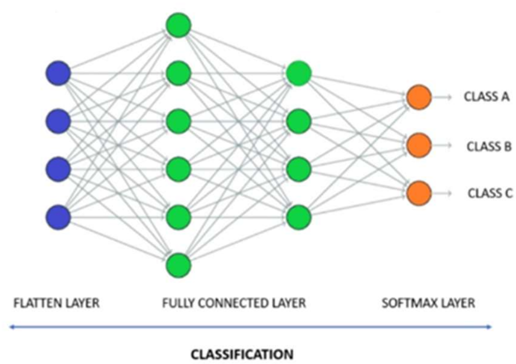

Fig 3: Fully Connected Layer

Hence, based on the above information, it is evident that the Convolutional Neural Network (CNN) model is an optimal choice for image recognition in assessing the health status of fruits due to its high accuracy.

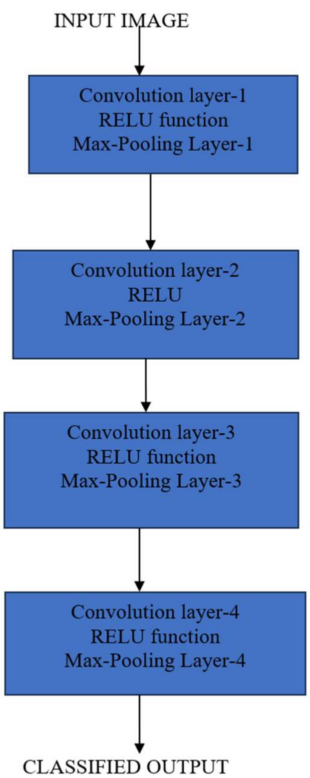

Fig 4: Architecture of proposed model

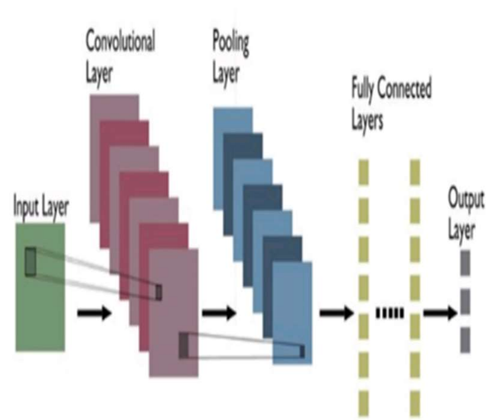

Fig5: CNN ARCHITECTURE

3.Implementation:
This process consists of these 4 steps which are discussed below

3.1) Collection of images dataset
For this project we have used data from the Kaggle data set named Breast Histopathology Images which consisted of 2 directories 0 and 1.
Each directory consisted of 479 images and 70 images of mammogram images as either benign and malignant

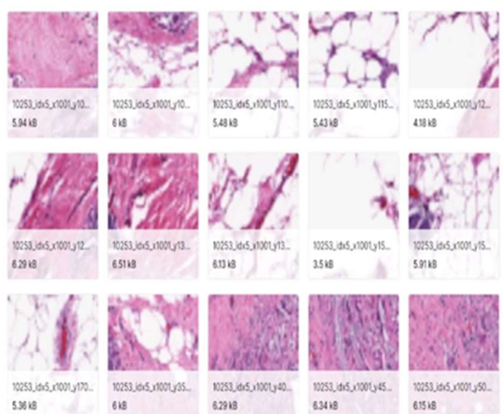

Fig6: collected dataset

3.2) Images pre-processing
Before starting to build the CNN model all the images are processed to change its size and other attributes.

All images have been resized into 100x100 pixels and a batch size of 32 has been taken.

We have used random flip on layers which is used to randomly flip the input data horizontally and vertically.

We have used Random Rotation layer which randomly rotates the input data by a given degree. We have given a rotation range of 0.5 radians (approximately 28.65 degrees).

3.3) CNN Modeling

At this point, the dataset has been split into two. Each of the dataset is split into 80% ,20% for training, testing the models, respectively

The developed model consists of two convolutional layers with Rectified Linear Unit (Re-LU) activation function, one max-pooling layer, a single flatten layer, and two dense layers. The model uses Adam optimizer and SoftMax function.

The total trainable parameter was 682,306 parameters. The developed model architecture is described below.

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_2 (Conv2D)            (None, 22, 22, 32)        1568
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 19, 19, 32)        16416
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 9, 9, 32)          0
_________________________________________________________________
dropout (Dropout)            (None, 9, 9, 32)          0
_________________________________________________________________
flatten_2 (Flatten)          (None, 2592)              0
_________________________________________________________________
dense_4 (Dense)              (None, 256)               663808
_________________________________________________________________
dense_5 (Dense)              (None, 2)                 514
=================================================================
Total params: 682,306
Trainable params: 682,306
Non-trainable params: 0
_________________________________________________________________
```

3.4) Model Evaluation

The developed model has undergone evaluation during the model testing process. This evaluation primarily focused on generating a classification report, which provides valuable insights into the performance of the models. Here the classification report consists of precision, recall, f1-score where we are getting the accuracies that is precision, recall and f1-score for each category of fruit separately.

4.Result:

Thus, up to this point we have trained the model with the above dataset and developed a model which has been evaluated by using loss function called sparse Categorical cross entropy function. Adam optimizer and accuracy metrics. On evaluating the model, we have a test loss of 3.65 percent and a test accuracy of 84.5 percent. The comparison result of training and validation accuracy as well as training and validation loss is shown below.

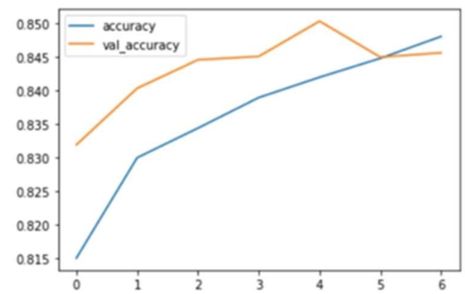

Fig7: comparison between training data and validation data accuracy

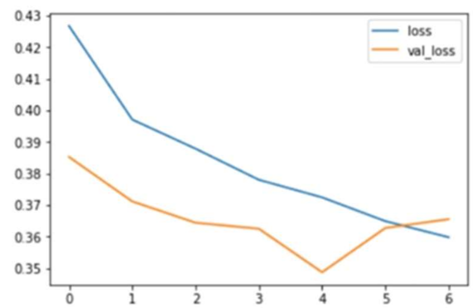

Fig 8: comparison between training data and validation data loss

Now to check whether the model is working accurately or not we have tested a few images and the result was accurate.

6.Conclusion:

In conclusion, the classification of breast cancer using Convolutional Neural Networks (CNN) is a promising approach that capitalizes on the capabilities of deep learning and image processing techniques. This project showcases the potential to revolutionize breast cancer diagnosis by providing automated and accurate classification. By training CNN models on diverse datasets of mammogram images, the project enables the extraction of relevant features for precise classification and prediction of breast cancer presence. CNNs offer several advantages, including their ability to learn intricate patterns and generalize well to unseen mammogram samples. The outcomes of this project have profound implications in the field of breast cancer detection, facilitating early diagnosis and personalized treatment. By enabling efficient and reliable classification, the project has the potential to improve patient outcomes, optimize treatment planning, and reduce healthcare costs. Future research and development can focus on refining the CNN models, expanding the dataset to encompass a wider range of breast cancer types and stages, and exploring the integration of real-time image analysis for practical clinical applications. Overall, the classification of breast cancer using CNNs holds great promise in enhancing breast cancer detection, advancing patient care, and addressing the challenges faced in the fight against breast cancer .

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