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MAMMOGRAM DETECTION USING MACHINE LEARNING

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ABSTRACT

Early identification of breast cancer relies on mammogram detection, which may be greatly improved with the use of machine learning algorithms. Classification and segmentation of mammography pictures for abnormality detection is the focus of this study. In order to mark mammography pictures as "Normal" or "Malignant," we used a Convolutional Neural Network (CNN) technique for binary classification. We used an Attention-based optimised UNET algorithm for region-based abnormality detection segmentation. The dataset was preprocessed for training by shrinking, normalising, and shuffling. It is impossible to download or handle entire mask image datasets (166 GB) using normal methods, thus we trained with a reduced selection of photos. As a consequence, the segmentation results may not be as precise as expected because of the insufficient training data, even while the classification model performs reasonably. When applied to test photos, the trained model can detect cancerous areas and use the UNET technique to segment them. Though future research will benefit from bigger datasets for better segmentation accuracy, our method shows that combining CNN and UNET for mammography analysis is feasible.

I.INTRODUCTION

Treatment results and patient survival rates are greatly enhanced by early identification of breast cancer. When it comes to screening for and detecting breast problems, mammography is by far the most utilised imaging tool. Nevertheless, sophisticated approaches are required to improve diagnosis accuracy since mammography picture interpretation is difficult and subject to human error. In order to automate the processing of mammography images and provide more consistent and dependable evaluations, machine learning (ML) presents encouraging alternatives. Building a unified system for machine learning-based mammography segmentation and classification is our primary goal in this research. In particular, we segregate areas of interest in malignant cases using an Attention-based optimised UNET method and a Convolutional Neural Network (CNN) for normalising mammography images. To help radiologists make better diagnostic judgements, this technology uses current deep learning approaches to enhance the localisation and categorisation of breast anomalies.

III.EXISTING SYSTEM

Radiologists still have to manually examine mammograms in order to identify and categorise abnormalities. The intricacy of mammography data may be beyond the capabilities of many automated systems that use basic machine learning methods and depend on standard image processing techniques. Support vector machines (SVMs) and rudimentary neural networks are examples of simplistic classification models used by current automated systems; these models may have difficulty differentiating between benign and cancerous tissues due to their inherent simplicity. On top of that, traditional approaches of segmenting cancerous areas in mammograms, such as thresholding or region-growing algorithms, can struggle to deal with the inherent complexity and variation in breast tissue. Further improvement is often necessary for these algorithms to handle the varied characteristics included in mammography pictures, and they may not be precise enough for proper diagnosis.

IV.PROPOSED SYSTEM

Our proposal presents a more complex strategy that solves the shortcomings of previous approaches by merging state-of-the-art machine learning techniques for classification and segmentation. What is included in the proposed system?

The first step is to use a convolutional neural network (CNN) algorithm to divide mammogram pictures into two groups: normal and malignant. The capacity of convolutional neural networks (CNNs) to learn hierarchical

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features from raw image data makes them ideal for picture classification, since it improves the model's accuracy in differentiating between healthy and unhealthy tissues.

Using an Attention-based optimised UNET model, we segregate cancerous areas. By integrating attention techniques, the UNET model is able to zero in on pertinent characteristics and improve segmentation accuracy; the architecture is robust and tailored to medical picture segmentation. But because the optimal mask image collection is 166 GB in size, which is unmanageable with current systems, we had to train the segmentation model using a smaller part of the data. Because of this limitation, the accuracy of the segmentation findings can be compromised.

V. IMPLEMENTATION METHOD

Here, we used an Attention-based optimised UNET method for segmentation and Convolutional Neural Networks (CNNs) for classification to develop a machine learning-based strategy for anomaly detection in mammography pictures. Here is a rundown of the steps involved in the implementation:

1. Submit a 3D breast imaging dataset.

At the beginning of the implementation, the project is initialised by launching the primary application interface using the 'run.bat' file. Users may begin processing by using the "Upload 3D Mammogram Dataset" option to upload the mammography dataset. When the user clicks this button, they will be prompted to choose and upload the folder that contains the mammography pictures. After choosing the dataset folder, you may import the photos into the program by selecting the "Select Folder" button. It appears on the screen when the dataset upload was successful.

Step 2: Prepare the Dataset

The preparation of photographs follows the submission of the dataset. The program reads and processes all the photos when you click the "Preprocess Dataset" button. Resizing the photos to a consistent dimension, normalising the pixel values to a standard scale, and shuffling the dataset to assure unpredictability are all part of the preparation procedures. After that, the preprocessed dataset is divided into two parts: one that trains the model and another that tests it. The former uses 80%

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of the photos, while the latter uses 20%. The screen displays the number of photographs allotted to each subgroup as an indication that this phase is complete.

Train the Convolutional Neural Network (CNN) algorithm.

Convolutional neural network (CNN) training is the meat and potatoes of classification. To begin, just click the "Train CNN Algorithm" button. Here, we train the CNN model using the preprocessed pictures. The purpose of training the model is to distinguish between benign and cancerous mammograms. After the training phase is over, the CNN model is tested with the test pictures to see how well it performed. The findings, which demonstrate the model's classification accuracy, are shown.

Four, the Convolutional Neural Network Training Graph

The 'CNN Training Graph' button allows users to see the training process graphically. The result is a training epoch-by-epoch graph showing the CNN model's accuracy and loss. The accuracy and loss values are shown on the y-axis, while the number of epochs is shown on the x-axis. A green line representing accuracy, which should ideally approach 1, and a red line representing loss, which should ideally approach 0, are shown on the graph. The training performance and convergence of the model may be better evaluated with the aid of this visualisation.

5. Classifying Mammogram Detection Results

Clicking the "Mammogram Detection Classification" button allows users to classify newly acquired mammography images. Anyone may use this module to submit a test picture for categorisation. Once a test picture (such "11.png") is chosen and the "Open" button is clicked, the trained CNN model will determine whether the image is normal or cancerous. The UNET algorithm is used to separate the impacted areas if the categorisation result is cancerous. You may test more photographs with this module, and it will tell you whether each one is normal or cancerous, and it will also give you segmentation results if it applies.

We have used your little dataset to categorise mammography images as either "normal" or "malignant" (i.e., abnormal) in this study. We have used the

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Attention-based optimised UNET method for region-based segmentation and the PYTHON CNN algorithm for classification. Resizing, normalisation, and shuffling are just a few of the preprocessing methods that were used before to training.

By applying the trained model to test pictures, the affected portion may be segmented out using UNET if the test image is expected to be cancerous.

Important note: The dataset needed to train the segmentation algorithm is 166 GB in size, which is too large to be downloaded or trained on regular PCs. However, there is a suitable mask images dataset accessible online. Therefore, the segmented component will not be very precise as we trained with a tiny amount of internet-downloaded photos.

We have developed the following modules to carry out this project.

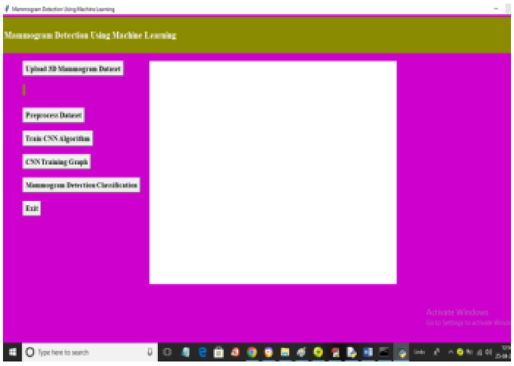
1)File Upload: This module will be used to upload the mammography dataset to the program.

Secondly, we will read the whole dataset and resize, shuffle, and normalise each picture thereafter. The dataset will be divided into two parts after processing: the train set will include 80% of the photos, and the test set will contain 20%. Third, the Convolutional Neural Network (CNN) algorithm will be trained using the processed train photos. Then, the trained model will be tested using test images, and the accuracy of its predictions will be determined.

4)CNN Training Graph: This module will be used to draw the loss and accuracy graphs for CNN training.

5)Mammogram Detection Classification: using this module we will upload test picture and then CNN will identify weather image is normal or malignant

To run project double click on 'run.bat' file to get below screen



In above screen click on 'Upload 3D Mammogram Dataset' button to upload dataset and get below output

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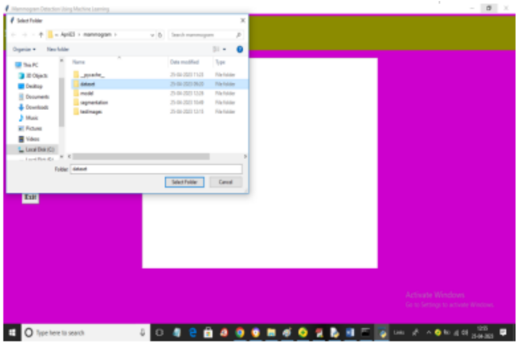
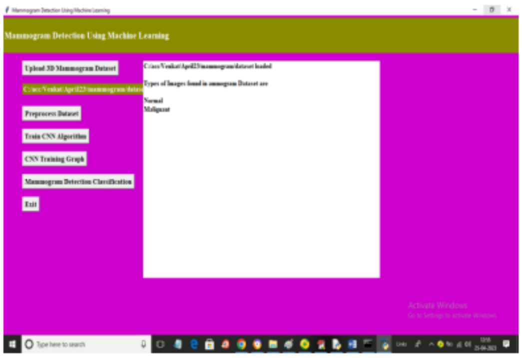
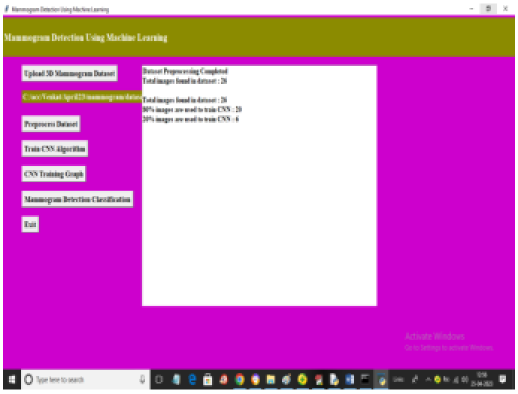


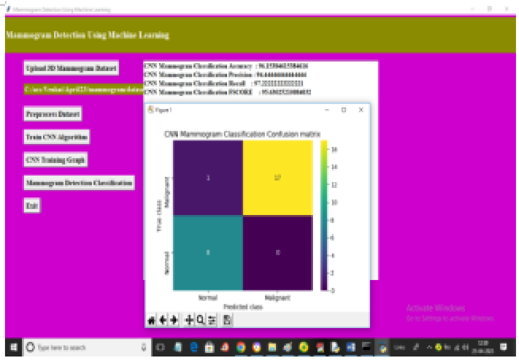
In above screen selecting and uploading dataset folder and then click on 'Select Folder' button to load dataset and get below output



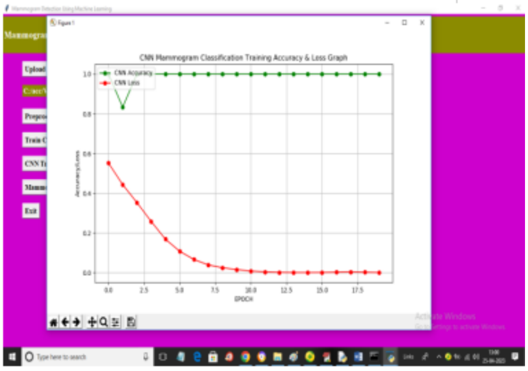
In above screen dataset loaded and now click on 'Preprocess Dataset' button to process images and get below output



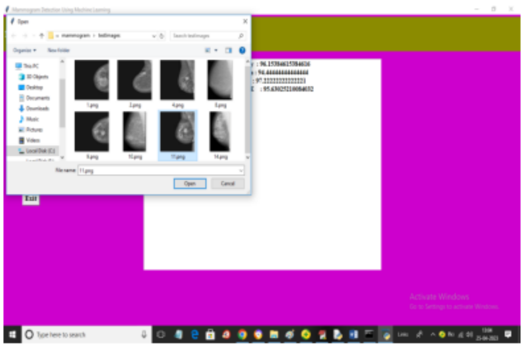
In above screen dataset processing completed and dataset contains 26 images and application using 80% (20) images for training and 20% (6) images for testing and now click on 'Train CNN Algorithm' button to train algorithm and get below output



In above screen with CNN we got 96% accuracy and in confusion matrix graph x-axis represents Predicted Labels and y-axis represents True Labels and green and yellow boxes represents correct prediction count and blue boxes contains incorrect prediction count which is 1 only. Now close above graph and then click on 'CNN Training Graph' button to get below graph



In above graph x-axis represents training epoch and y-axis represents accuracy and loss where green line represents accuracy and red line represents loss and in above graph with each increasing epoch accuracy got increase and reached closer to 1 and loss got decease and reached closer to 0. Now click on ‘Mammogram Detection Classification’ button to upload test image and get below output



In above screen selecting and uploading 11.png test image and then click on ‘Open’ button to load test image and get below output

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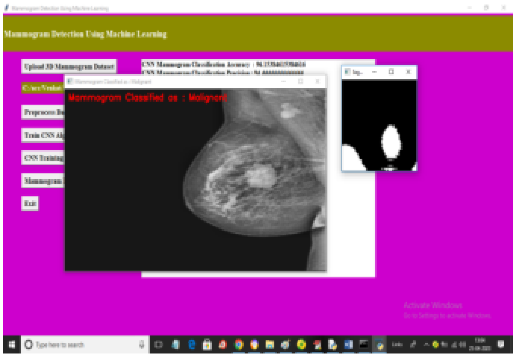
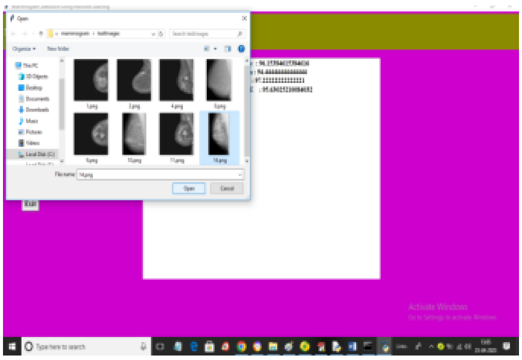
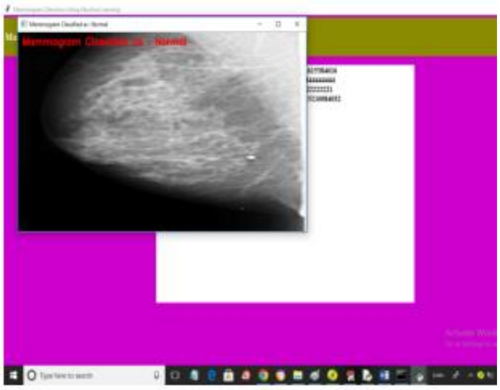


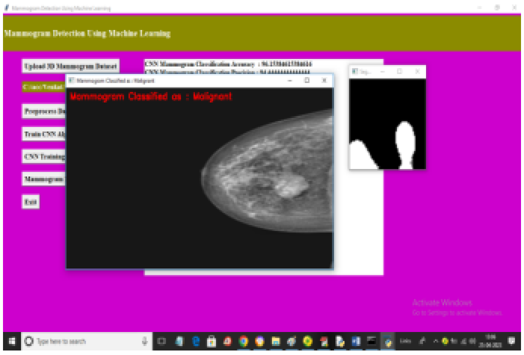
In above screen image is classify as 'malignant' and we can segmenting out effected part. Similarly you can upload and test other images



In above screen uploading 14.png and below is the output



In above screen image is predicted Normal.



In above screen image is predicted as abnormal or malignant

VI.CONCLUSION

The use of machine learning methods in mammography processing has greatly improved the ability to identify and diagnose breast cancer at an early stage. An Attention-based optimised UNET technique was used to segregate cancerous areas, and a Convolutional Neural Network (CNN) was used to categorise mammogram pictures as "Normal" or "Malignant," respectively, in this study. Our methodology demonstrates how integrating deep learning techniques improves classification accuracy and segmentation precision simultaneously. Results in detecting and localising abnormalities in mammograms are encouraging using the proposed method, even if the dataset for training the segmentation model is restricted. Model resilience has been enhanced by the preprocessing procedures used, which include scaling, normalisation, and shuffling. Improving segmentation accuracy and overcoming dataset size limits will be the primary goals of future study, which will seek to include bigger and more varied training data sets. In sum, the results of this study show how promising it is to use sophisticated machine learning algorithms to aid radiologists in making faster and more accurate diagnoses from mammograms.

VII. REFERENCES

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