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MAMMOGRAM DETECTION USING MACHINE LEARNING

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ABSTRACT

Mammogram detection plays a critical role in early breast cancer diagnosis, and leveraging machine learning techniques can significantly enhance diagnostic accuracy. This project addresses the classification and segmentation of mammogram images to identify abnormalities. We employed a Convolutional Neural Network (CNN) algorithm for binary classification to categorize mammogram images as either 'Normal' or 'Malignant'. For region-based segmentation of detected abnormalities, we utilized an Attention-based optimized UNET algorithm. The preprocessing phase included resizing, normalization, and shuffling of the dataset to prepare it for training. Due to the large size of comprehensive mask image datasets (166 GB), which are impractical to download or process with standard systems, we used a smaller subset of images for training. Consequently, while the classification model performs with reasonable accuracy, the segmentation results may exhibit limited precision due to the constrained training data. The trained model can be applied to test images, where malignant predictions trigger segmentation of the affected regions using the UNET algorithm. This approach demonstrates the feasibility of integrating CNN and UNET for mammogram analysis, though future work will benefit from access to larger datasets for improved segmentation accuracy.

I.INTRODUCTION

Early detection of breast cancer significantly improves treatment outcomes and patient survival rates. Mammography is a widely used imaging technique for screening and diagnosing breast abnormalities. However, interpreting mammogram images can be challenging and prone to human error, necessitating advanced methods to enhance diagnostic accuracy. Machine learning (ML) offers promising solutions for automating the analysis of mammogram images, providing more consistent and reliable assessments. In this project, we aim to develop an integrated system for mammogram classification and segmentation using machine learning techniques. Specifically, we use a Convolutional Neural Network (CNN) for classifying mammogram images as either 'Normal' or 'Malignant' and employ an Attention-based optimized UNET algorithm for segmenting regions of interest in malignant cases. This approach leverages modern deep learning methodologies to improve both the classification and localization of breast abnormalities, ultimately aiding radiologists in making more informed diagnostic decisions.

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III.EXISTING SYSTEM

Current methods for mammogram analysis typically involve manual review by radiologists, who interpret images to detect and classify abnormalities. Although automated systems have been developed, many rely on traditional image processing techniques and basic machine learning algorithms that may not fully capture the complexity of mammogram data. Existing automated systems often use simple classification models, such as support vector machines (SVMs) or basic neural networks, which may struggle with distinguishing subtle differences between normal and malignant tissues. Additionally, segmentation of malignant regions in mammograms is usually performed using conventional methods like thresholding or region-growing techniques, which may not effectively handle the variability and intricacies of breast tissue. These systems may lack the precision needed for accurate diagnosis and often require further refinement to handle the diverse features present in mammogram images.

IV.PROPOSED SYSTEM

To address the limitations of existing methods, our project proposes a more sophisticated approach combining advanced machine learning algorithms for both classification and segmentation tasks. The proposed system includes:

1. Classification Using Convolutional Neural Network (CNN): We implement a CNN-based algorithm to classify mammogram images into two categories: 'Normal' and 'Malignant'. CNNs are well-suited for image classification due to their ability to learn hierarchical features from raw image data, improving the model's accuracy in distinguishing between normal and abnormal tissues.
2. Segmentation Using Attention-Based Optimized UNET: For the segmentation of malignant regions, we utilize an Attention-based optimized UNET model. UNET is a powerful neural network architecture specifically designed for medical image segmentation, and incorporating attention mechanisms helps the model focus on relevant features and enhance segmentation accuracy. However, due to the large size of the ideal mask image dataset (166 GB), which is not feasible to process with standard systems, we trained the segmentation model on a smaller subset of available images. This constraint may affect the precision of the segmentation results.

V. IMPLEMENTATION METHOD

In this study, we implemented a machine learning-based approach for detecting abnormalities in mammogram images using Convolutional Neural Networks (CNN) for classification and an Attention-based optimized UNET algorithm for segmentation. The following sections detail the implementation process:

1. Upload 3D Mammogram Dataset

The implementation begins by initializing the project through the `run.bat` file, which brings up the main application interface. To begin processing, users first upload the mammogram dataset by selecting the 'Upload 3D Mammogram Dataset' button. This action prompts the user to choose and upload the folder containing the mammogram images. Once the dataset folder is selected, clicking the 'Select Folder' button loads the images into the application. Successful dataset upload is confirmed on the screen.

2. Preprocess Dataset

Following dataset upload, the next step involves preprocessing the images. By clicking on the 'Preprocess Dataset' button, the application reads and processes all the images. The preprocessing steps include resizing the images to a uniform dimension, normalizing pixel values to a standard scale, and shuffling the dataset to ensure randomness. The preprocessed dataset is then split into training and testing subsets, with 80% of the images used for training the model and 20% for testing. The completion of this step is indicated on the screen, detailing the number of images allocated for each subset.

3. Train CNN Algorithm

The core of the classification process involves training the CNN algorithm. Users initiate this by selecting the 'Train CNN Algorithm' button. This step involves feeding the preprocessed training images into the CNN model. The model is trained to differentiate between normal and malignant mammogram images. Upon completion of the training phase, the CNN model is evaluated using the test images to determine its accuracy. The results are displayed, showing the classification accuracy of the model.

4. CNN Training Graph

To visualize the training process, users can click on the 'CNN Training Graph' button. This generates a graph illustrating the CNN model's accuracy and loss over training epochs. The x-axis represents the number of epochs, while the y-axis displays accuracy and loss values. The graph features two lines: a green line for accuracy, which ideally approaches 1, and a red line for loss, which ideally approaches 0. This visualization helps in assessing the model's performance and convergence during training.

5. Mammogram Detection Classification

For the classification of new mammogram images, users click on the 'Mammogram Detection Classification' button. This module allows users to upload a test image for classification. After selecting a test image (e.g., `11.png`) and clicking the 'Open' button, the trained CNN model predicts whether the image is normal or malignant. If the classification result is malignant, the affected regions are segmented using the UNET algorithm. This module also enables testing additional images, with the results indicating whether each image is classified as normal or malignant, along with segmentation outputs where applicable.

In this project we have used your small dataset to classify mammogram image as 'Normal or Malignant (abnormal). For classification we are using PYTHON CNN algorithm and for region based segmentation we have used Attention based optimized UNET algorithm. Before training we have applied various Preprocessing techniques such as Resizing, normalization and shuffling.

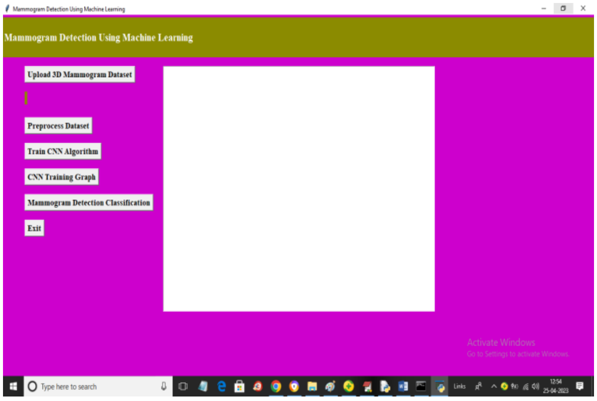
Trained model can be applied on test images and if test image predicted as malignant then effected part will be segmented out using UNET.

Note: To train segmentation algorithm we need proper mask images dataset but this dataset is available on internet with 166 GB size which cannot be downloaded or trained with normal systems. So we have trained with small number of images downloaded from internet so segmented part will not be little accurate.

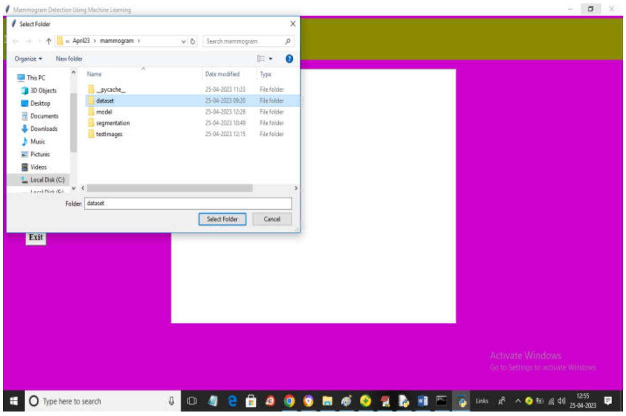
To implement this project we have designed following modules

1) Upload 3D Mammogram Dataset: using this module we will upload mammogram dataset to application
2) Preprocess Dataset: we will read all images and then resize, shuffle and normalize all images. After processing dataset will be split into train and test where application will be using 80% images for training and 20% for testing
3) Train CNN Algorithm: processed train images will be input to CNN algorithm to train a model and test images will be applied on trained model to calculate prediction accuracy
4) CNN Training Graph: using this module we will plot CNN training accuracy and loss graph
5) Mammogram Detection Classification: using this module we will upload test image and then CNN will classify weather image is normal or malignant

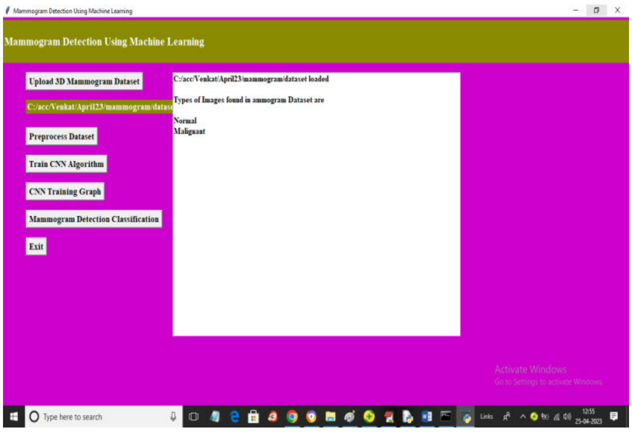
To run project double click on 'run.bat' file to get below screen



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



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

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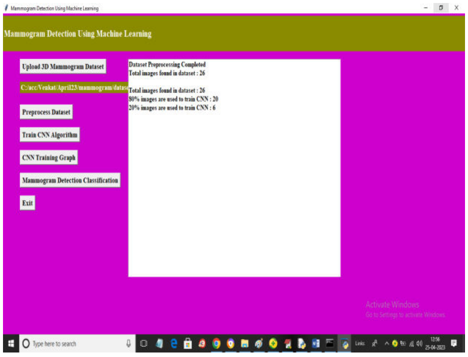
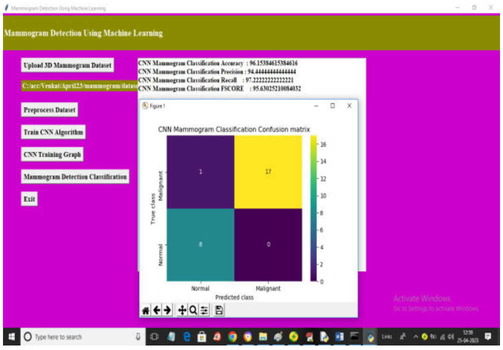
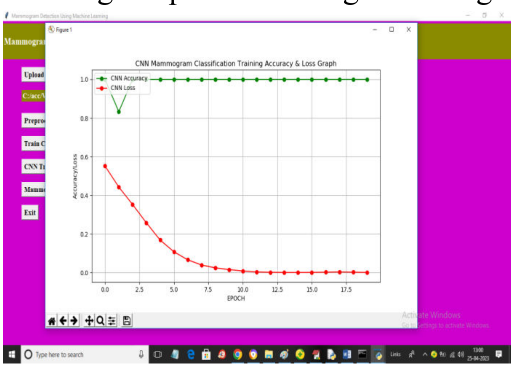


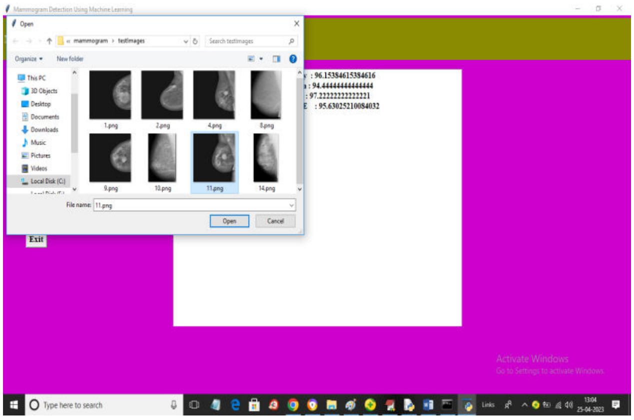
In above screen dataset processing completed and dataset contains 26 images and application using 80% (20) images for training and 20% (6) images for testing and now click on 'Train CNN Algorithm' button to train algorithm and get below output



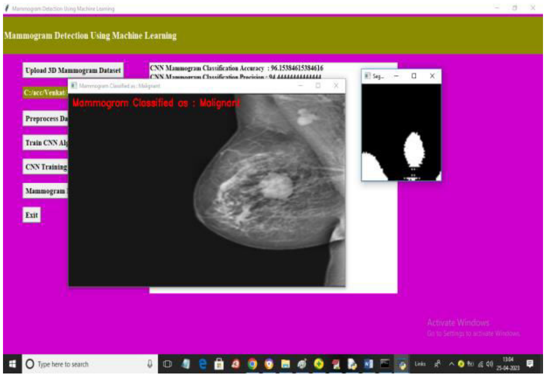
In above screen with CNN we got 96% accuracy and in confusion matrix graph x-axis represents Predicted Labels and y-axis represents True Labels and green and yellow boxes represents correct prediction count and blue boxes contains incorrect prediction count which is 1 only. Now close above graph and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



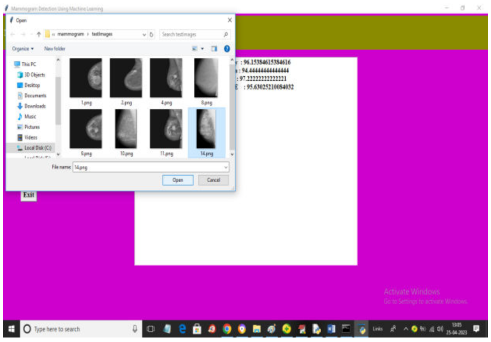
In above graph x-axis represents training epoch and y-axis represents accuracy and loss where green line represents accuracy and red line represents loss and in above graph with each increasing epoch accuracy got increase and reached closer to 1 and loss got decease and reached closer to 0. Now click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



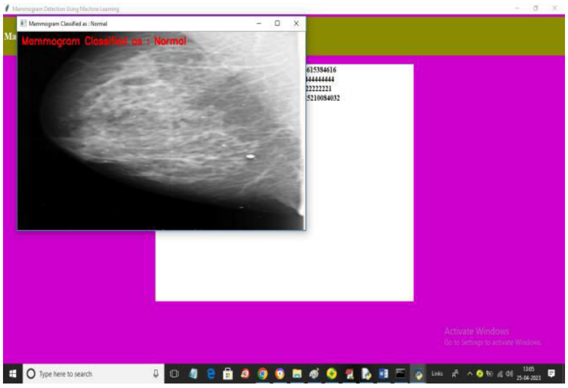
In above screen selecting and uploading 11.png test image and then click on 'Open' button to load test image and get below output



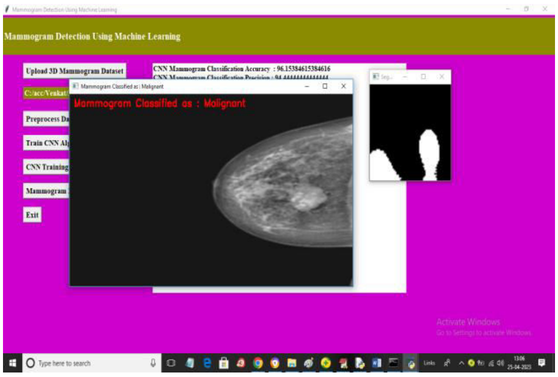
In above screen image is classify as 'malignant' and we can segmenting out effected part. Similarly you can upload and test other images



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



In above screen image is predicted as Normal.



In above screen image is predicted as abnormal or malignant

VI.CONCLUSION

The integration of machine learning techniques into mammogram analysis represents a significant advancement in the early detection and diagnosis of breast cancer. This project has successfully implemented a Convolutional Neural Network (CNN) for classifying mammogram images as 'Normal' or 'Malignant', and an Attention-based optimized UNET algorithm for segmenting malignant regions. Our approach demonstrates the effectiveness of combining deep learning methods to enhance both classification accuracy and segmentation precision. Despite the constraints posed by the limited dataset for training the segmentation model, the proposed system shows promising results in identifying and localizing abnormalities in mammograms. The preprocessing techniques applied, including resizing, normalization, and shuffling, have contributed to the robustness of the models. Future work will focus on addressing the limitations related to the dataset size and improving the segmentation accuracy by incorporating larger and more diverse training data. Overall, this project highlights the potential of leveraging advanced machine learning algorithms to improve mammogram analysis and support radiologists in providing more accurate and timely diagnoses.

VII. REFERENCES

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