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A HYBRID DEEP LEARNING APPROACH FOR BREAST CANCER DETECTION USING CNN AND RNN

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ABSTRACT

Breast cancer remains one of the most prevalent cancers among women worldwide, making early detection essential for effective treatment. This paper presents a novel approach to breast cancer detection using a hybrid architecture that combines Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN). By harnessing the strengths of CNNs for feature extraction and RNNs for sequence analysis, this hybrid model aims to enhance the accuracy and efficiency of breast cancer detection from medical imaging data. In our approach, the CNN component extracts meaningful features from mammogram images, widely used in breast cancer screening. These features are then processed by the RNN, which captures temporal dependencies and patterns in the data. This combination enables the model to leverage both spatial and temporal information, providing more accurate and reliable breast cancer detection. The key contributions of this work include the development of a CNN-RNN hybrid architecture specifically tailored for breast cancer detection and its comprehensive evaluation on an extensive mammogram dataset. Results show that our hybrid model outperforms traditional CNN and RNN models in both accuracy and efficiency, underscoring its potential for improving breast cancer detection in clinical applications.

INTRODUCTION

Breast cancer remains a leading cause of cancer-related deaths among women globally, underscoring the importance of early and precise detection for improving survival rates [1]. Detecting breast cancer in its early stages can significantly enhance treatment success, making early screening crucial. Traditional screening methods, such as mammography, are widely used in clinical settings for early detection. However, interpreting mammogram images can be challenging due to variations in breast tissue and the subtle nature of early-stage cancer indicators [2]. The advent of deep learning, especially Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), has brought remarkable advancements in medical image analysis, offering automated methods capable of processing complex image data with higher accuracy [3]. Deep learning approaches, particularly CNNs, have proven effective in capturing intricate spatial features in images. This capability is particularly beneficial for tasks like breast cancer detection, where detailed analysis of tissue patterns can reveal early signs of malignancy [4]. CNNs have emerged as a powerful tool in image analysis by automatically identifying hierarchical features from images without requiring manual feature extraction [5]. Through multiple layers of convolution and pooling, CNNs can recognize intricate spatial patterns, which are critical in identifying cancerous tissues in medical imaging [6]. This makes CNNs an ideal choice for breast cancer detection applications. However, CNNs are not without limitations. While they excel at spatial feature extraction, they are less capable of capturing temporal dependencies, which can be essential for detecting changes or patterns that emerge over time [7]. In the context of breast cancer, the ability to analyze temporal data is valuable, especially for tracking the progression or recurrence of disease across multiple screenings. RNNs are well-suited for handling sequential data, as they can recognize temporal patterns and dependencies that single-frame image analysis might overlook [8]. This capability can be especially valuable in medical imaging, where a sequence of images or a patient's history of scans may reveal critical diagnostic information [9]. By integrating CNNs with RNNs, it is possible to develop a hybrid model that leverages both spatial and temporal information, enhancing the overall accuracy and reliability of breast cancer detection [10]. This paper proposes a hybrid model combining CNN and RNN architectures, designed to capture both spatial and sequential features for a comprehensive approach to breast cancer detection [11]. The CNN component of the model is responsible for extracting spatial features from mammogram images, which are a primary tool in breast cancer screening. These features are then processed by the RNN component, which captures temporal dependencies and patterns within the data. This integration allows the model to analyze both types of information, enhancing its ability to detect breast cancer accurately [12].

The hybrid CNN-RNN model presented in this paper aims to address some of the key challenges in breast cancer detection.

Mammogram images can contain noise and complex textures, which make distinguishing between benign and malignant tissue challenging [13]. In addition, manual interpretation of mammograms by radiologists can lead to variability in diagnosis, with potential for false positives or false negatives. For instance, dense breast tissue can obscure early-stage abnormalities, making them difficult to detect. Traditional machine learning methods have struggled with these challenges, as they typically rely on manual feature engineering, which can be labor-intensive and prone to human error [14]. The adoption of deep learning methods, specifically CNNs and RNNs, offers a promising solution to these challenges by providing automated systems that can accurately interpret mammogram images and reduce the burden on healthcare professionals [15]. Deep learning models like CNNs eliminate the need for manual feature selection by automatically learning the most relevant features for cancer detection. This capability is particularly valuable for complex medical images, where minute spatial details can be critical for identifying abnormalities. CNNs have been extensively used in breast cancer detection with high success, achieving impressive performance metrics in both accuracy and efficiency. However, due to their limitations in capturing temporal relationships in sequential data, CNNs may miss certain patterns that emerge over time. The RNN component in the hybrid model addresses this by processing sequential data and capturing dependences that may indicate cancer progression or recurrence.

LITERATURE SURVEY

The field of breast cancer detection has significantly evolved with advancements in machine learning and deep learning, offering potential for improving early diagnosis and treatment outcomes. Traditionally, mammography has been the primary screening tool for breast cancer, allowing for non-invasive imaging of breast tissues. Although mammography is widely used, its effectiveness is often limited by high rates of false positives and negatives, particularly in dense breast tissues where subtle signs of malignancy can be obscured. Early efforts to address these limitations relied on manual image interpretation by radiologists, which is prone to human error and can vary widely among practitioners. These challenges in manual interpretation have driven the development of automated methods using machine learning and, more recently, deep learning approaches, which can analyze large volumes of imaging data with greater consistency and precision. Deep learning, particularly Convolutional Neural Networks (CNN), has shown remarkable success in medical imaging. CNNs are well-suited for image analysis due to their ability to automatically learn and extract hierarchical features from raw image data. In breast cancer detection, CNNs have been widely applied to analyze mammogram images, with various architectures achieving notable accuracy in identifying potential malignancies. CNNs operate by capturing spatial features from images, making them highly effective for tasks that rely on detailed visual information, such as identifying tumor shapes, sizes, and textures. The success of CNNs in breast cancer detection has motivated further research into optimizing CNN architectures and applying them to increasingly complex medical imaging datasets. However, while CNNs excel in extracting spatial features from static images, they may not be as effective in capturing sequential or temporal information, which can be critical when analyzing patterns over time or across multiple image frames.

In addition to CNNs, Recurrent Neural Networks (RNN) have emerged as valuable tools for handling sequential data, making them well-suited for applications that require temporal analysis. RNNs have proven effective in natural language processing and time-series forecasting due to their ability to retain information across time steps, capturing temporal dependencies in data. This capability is particularly relevant for medical imaging applications where sequential analysis can offer additional insights. In breast cancer detection, RNNs are beneficial when examining a sequence of mammogram images over time, as they can help detect subtle changes that may indicate disease progression or recurrence. However, RNNs alone are generally not as effective in processing high-dimensional image data, which is where CNNs excel. This complementarity has led researchers to explore hybrid models that combine CNNs and RNNs, leveraging CNNs for spatial feature extraction and RNNs for temporal pattern analysis, creating a more holistic approach to medical image analysis. The development of hybrid CNN-RNN architectures in breast cancer detection is based on the premise that both spatial and temporal information are valuable for comprehensive diagnosis. In this hybrid approach, CNNs first process the mammogram images to extract spatial features that are then passed to the RNN, which captures any temporal dependencies within the data. This two-stage process allows the model to fully utilize the strengths of each neural network type, potentially leading to improved accuracy and reliability. Studies on hybrid CNN-RNN models in other medical imaging domains have demonstrated that combining spatial and temporal information can enhance the model's ability to distinguish between normal and abnormal tissues, providing a more robust diagnostic tool compared to standalone CNN or RNN architectures. This approach is especially useful in cases where a patient's imaging data spans multiple time points, allowing the model to learn from both current and historical data, which can improve early detection and treatment planning.

One of the main challenges in developing hybrid CNN-RNN models for breast cancer detection is the need for large, annotated datasets. Training deep learning models, especially hybrid architectures, requires extensive data to prevent overfitting and to ensure the model can generalize well to new, unseen data. In breast cancer detection, mammogram datasets must be carefully labeled to distinguish between benign and malignant findings, which can be a resource-intensive process. Additionally, medical imaging data often contains noise and variability due to differences in equipment, imaging protocols, and patient anatomy, making it difficult for models to learn consistent patterns. To address these challenges, researchers often employ data augmentation techniques, such as rotation, scaling, and flipping, to artificially expand the dataset and improve model robustness. Transfer learning, where models pre-trained on large datasets are fine-tuned on specific medical imaging data, is another approach used to improve model performance without requiring extensive annotated datasets. Evaluation metrics are critical in assessing the performance of breast cancer detection models. Metrics such as accuracy, sensitivity, specificity, and area under the receiver operating characteristic (ROC) curve are commonly used to measure a model's effectiveness. Sensitivity, in particular, is essential in cancer detection, as it reflects the model's ability to correctly identify true positives, ensuring that cancer cases are not missed. Specificity is also important, as it measures the model's ability to identify true negatives, reducing the likelihood of false positives, which can lead to unnecessary follow-up tests and patient anxiety. In studies of hybrid CNN-RNN models, these metrics are used to compare the performance of hybrid architectures against traditional CNN or RNN models. Findings indicate that hybrid models often outperform single-network models, demonstrating higher accuracy and improved balance between sensitivity and specificity, which are crucial for reliable cancer detection in clinical applications.

The deployment of hybrid deep learning models for breast cancer detection in real-world clinical settings requires additional considerations beyond model accuracy. Computational efficiency is essential, as processing mammogram images quickly and accurately is necessary for timely diagnosis. Hybrid models that combine CNNs and RNNs can be computationally intensive, so optimizing these models to run efficiently on standard medical imaging equipment is a key focus of ongoing research. Techniques such as model pruning, quantization, and the use of specialized hardware accelerators, like Graphics Processing Units (GPUs), can help improve model efficiency. Moreover, the interpretability of deep learning models is a critical consideration in healthcare, where model predictions must be explainable to gain the trust of clinicians and patients. Efforts to increase model transparency include visualization techniques, such as saliency maps and attention mechanisms, which highlight the regions of an image that influence the model's predictions. These techniques can help clinicians understand the model's reasoning, making it easier to integrate into existing diagnostic workflows. As hybrid CNN-RNN models continue to evolve, their potential applications in breast cancer detection are expanding. Future research is likely to explore the integration of other data types, such as patient medical histories, genetic information, and biopsy results, into hybrid models to improve diagnostic accuracy. Combining imaging data with non-imaging data can provide a more comprehensive view of a patient's health, potentially leading to personalized treatment plans. Another area of interest is the application of hybrid models in mobile or remote settings, where access to specialized medical equipment may be limited. By deploying optimized models on portable devices, breast cancer screening could become more accessible in underserved communities, addressing disparities in healthcare access and outcomes.

In summary, the literature on hybrid CNN-RNN models for breast cancer detection highlights the advantages of combining spatial and temporal information to improve diagnostic accuracy. The integration of CNNs for feature extraction and RNNs for sequence analysis offers a powerful approach to tackling the complexities of medical imaging data, with promising implications for breast cancer detection. While challenges such as dataset availability, computational demands, and model interpretability remain, ongoing advancements in deep learning and computational techniques are likely to make these models increasingly viable for clinical use. The development and application of hybrid deep learning models represent a significant step toward more accurate, efficient, and accessible breast cancer screening, with the potential to transform early diagnosis and treatment outcomes for women worldwide.

PROPOSED SYSTEM

The proposed system for breast cancer detection leverages the complementary strengths of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) to create a hybrid architecture that enhances diagnostic accuracy and reliability. Given that breast cancer detection often depends on subtle patterns in imaging data, particularly mammograms, the system's design focuses on optimizing both spatial and temporal data analysis capabilities. The CNN component in this system is responsible for feature extraction from mammogram images, which are widely used in breast cancer screening for their high-resolution representation of breast tissues. CNNs are highly adept at identifying spatial patterns within images, such as tumor boundaries, textures, and various anomalies, by learning hierarchical features through successive convolutional layers. This feature extraction process effectively transforms raw imaging data into a set of rich and representative features that highlight key areas of interest, ensuring that important diagnostic information is captured. Once the CNN has extracted spatial features from the mammogram images, the data is passed to the RNN component of the hybrid system. The RNN is utilized for its ability to capture temporal dependencies within sequential data, an attribute that is particularly relevant in cases where a series of images is available over time, such as for tracking the progression of a lesion or nodule. RNNs can retain and leverage information from previous frames in a sequence, enabling the system to make more informed and contextually aware predictions. In the context of breast cancer detection, the RNN interprets the extracted features as sequential data, detecting subtle patterns or changes that may indicate malignancy. This dual-stage processing—first extracting spatial features and then capturing temporal dependencies—enables the hybrid model to deliver a comprehensive analysis that incorporates both individual image detail and sequence-based insight, thus providing a more holistic understanding of the data.

To optimize the performance of this hybrid system, both the CNN and RNN components are tailored specifically for breast cancer detection. The CNN architecture comprises multiple convolutional layers followed by pooling layers, which reduce the spatial dimensions of the data while retaining essential features. These layers are then followed by fully connected layers, which consolidate the extracted features into a high-dimensional feature vector representing the image content in a compact format. In designing the CNN, considerations are made regarding kernel size, stride, and padding to ensure that the network effectively captures both small, localized patterns and larger structures within the mammogram images. Regularization techniques such as dropout and batch normalization are also implemented to prevent overfitting, which can occur when a model becomes too specialized to the training data and performs poorly on new, unseen data. By using these techniques, the CNN is able to generalize better and improve its performance across diverse mammogram datasets. The RNN component, which follows the CNN, is designed with a focus on maintaining a memory of prior observations, which is essential for capturing the progression or regression of cancerous growths. In this system, a type of RNN known as Long Short-Term Memory (LSTM) is employed. LSTMs are an advanced RNN variant that addresses the issue of vanishing gradients, which can impair a traditional RNN's ability to learn long-term dependencies. LSTMs have the capacity to remember long-term dependencies through a memory cell that selectively retains information over time, enabling the model to leverage past information effectively. This characteristic makes LSTMs particularly suitable for medical imaging tasks, where detecting changes over time can provide crucial information for diagnosing cancer. By incorporating LSTMs, the proposed system benefits from an enhanced ability to analyze time-series data, contributing to more accurate predictions by understanding the temporal context within mammogram sequences. Data preprocessing is a crucial aspect of the proposed system, as medical imaging data often contains noise and variability across different sources. The images are first standardized through preprocessing steps that include resizing, normalization, and, if necessary, noise reduction. Resizing ensures that all images are uniform in dimensions, which is essential for batch processing in neural networks. Normalization adjusts the pixel values to a common scale, improving the CNN's ability to learn consistent features across varying image intensities. Additionally, data augmentation techniques are applied to artificially increase the diversity of the training set. Techniques such as flipping, rotation, and zooming are used to simulate variations in mammogram images, thereby enhancing the model's robustness and helping it generalize better to new data. Through these preprocessing steps, the system ensures that the input data is optimized for feature extraction and minimizes the likelihood of model bias caused by inconsistencies in image quality or resolution.

The training phase of the proposed system is conducted on a large mammogram dataset that includes both benign and malignant cases, allowing the hybrid model to learn distinguishing features that indicate breast cancer. During training, the CNN-RNN hybrid model uses a supervised learning approach, where labeled data guides the learning process. A loss function, such as binary cross-entropy, is used to quantify the model's prediction accuracy, penalizing incorrect classifications and encouraging accurate predictions. The system is trained in an end-to-end manner, where both CNN and RNN components are optimized simultaneously, allowing them to complement each other effectively. Backpropagation is used to adjust the weights of the network, with optimization algorithms like Adam or SGD (Stochastic Gradient Descent) facilitating efficient convergence to an optimal solution. The model's performance is evaluated on a validation set to tune hyperparameters, ensuring that it maintains a balance between high accuracy and efficient processing times.

Upon training, the proposed system is evaluated through rigorous testing to ensure its effectiveness in a real-world clinical context. The hybrid model's performance is compared with traditional CNN-only and RNN-only models, with metrics such as accuracy, sensitivity, specificity, and F1-score providing insight into its diagnostic capabilities. Sensitivity is a critical metric for cancer detection, as it measures the model's ability to correctly identify malignant cases. Specificity, which reflects the model's accuracy in identifying benign cases, is also essential to minimize false positives. The results demonstrate that the CNN-RNN hybrid model achieves superior performance in both sensitivity and specificity, indicating its potential for reliable breast cancer detection. The comprehensive evaluation also includes a review of the model's computational efficiency, as practical applications require not only high accuracy but also the ability to process images swiftly to facilitate timely diagnoses.

In addition to performance metrics, the interpretability of the proposed system is an important consideration. Visualization techniques, such as heat maps generated by Grad-CAM (Gradient-weighted Class Activation Mapping), are employed to highlight the regions of the mammogram images that influence the model's predictions. This transparency enables clinicians to understand which features the model considers significant, building trust in the AI system and facilitating its integration into clinical workflows. Interpretability also allows for model validation by radiologists, who can confirm whether the highlighted regions align with their own assessments, thereby increasing confidence in the model's outputs. In conclusion, the proposed CNN-RNN hybrid system for breast cancer detection presents a comprehensive solution that integrates both spatial and temporal analysis of mammogram images. By combining CNNs for effective feature extraction with RNNs for sequence analysis, this system addresses the limitations of traditional models and provides a more accurate, robust, and interpretable diagnostic tool. Through meticulous training and evaluation, this hybrid model has demonstrated its potential to enhance breast cancer detection accuracy, offering significant promise for early diagnosis and improved patient outcomes in clinical settings. This system represents a significant step forward in applying deep learning to medical imaging, with potential applications extending beyond breast cancer to other domains where temporal and spatial data play a critical role in diagnosis.

METHODOLOGY

The methodology of this hybrid deep learning approach for breast cancer detection is structured to leverage the unique advantages of Convolutional Neural Networks (CNNs) for spatial feature extraction and Recurrent Neural Networks (RNNs) for temporal pattern recognition. This combination provides a comprehensive analysis by capturing essential spatial features from mammogram images and temporal dependencies across sequences. The process begins with data collection, where a large dataset of mammogram images is compiled. These images are essential for training the model to distinguish between benign and malignant cases effectively. To ensure that the data is suitable for deep learning, preprocessing steps are applied to standardize and enhance the quality of the images. Each image is resized to a uniform dimension, which allows consistent input dimensions for the CNN. Normalization of pixel values is conducted to bring the data into a common scale, reducing the risk of biases introduced by variations in lighting or imaging conditions. Additionally, data augmentation techniques are used to increase dataset diversity by artificially creating variations of existing images through transformations such as rotation, flipping, and zooming, which improves the model's ability to generalize to unseen data. Once the data is preprocessed, it is divided into training, validation, and testing sets to ensure that the model can be effectively trained and evaluated. The training set is used to teach the model, while the validation set assists in hyperparameter tuning, and the test set provides an unbiased assessment of the model's performance. The methodology then proceeds to the CNN design, focusing on building an architecture capable of extracting intricate spatial features from mammogram images. This CNN consists of several convolutional layers that use filters to detect features such as edges, textures, and shapes, which are important for identifying breast tissue patterns. Each convolutional layer is followed by an activation function, commonly ReLU, to introduce non-linearity, allowing the model to learn complex patterns. Pooling layers are included to down-sample the data, reducing its spatial dimensions while retaining significant features. This reduces computational load and prevents overfitting by ensuring the network does not rely heavily on specific spatial positions. The convolutional and pooling layers are followed by fully connected layers that consolidate the extracted features into a final feature vector, which represents the image content in a compact form.

Once the CNN has transformed each image into a feature vector, the data is passed to the RNN component of the hybrid model. The RNN architecture, designed using Long Short-Term Memory (LSTM) cells, processes these feature vectors as a sequence, allowing it to capture temporal dependencies. LSTM cells are particularly effective in managing long-term dependencies, addressing the vanishing gradient issue common in traditional RNNs. This capacity is crucial in medical imaging, where subtle temporal changes in a sequence of images may indicate disease progression. The RNN processes each feature vector over time steps, learning to recognize patterns across multiple images. This enables the hybrid model to interpret not only isolated features in each mammogram but also their progression or regression over time, enhancing detection accuracy. The data flow between CNN and RNN is managed to ensure that the spatial and temporal features complement each other effectively, allowing the model to make predictions based on both aspects. The next step involves training the hybrid CNN-RNN model using supervised learning. During training, the model is fed labeled mammogram images from the training dataset. The loss function, typically binary cross-entropy for binary classification tasks, calculates the difference between the model's predictions and the actual labels, generating a loss value that quantifies prediction error. Backpropagation is used to adjust the weights of the CNN and RNN components, minimizing the loss function and improving accuracy with each iteration. Optimization algorithms, such as Adam or Stochastic Gradient Descent (SGD), are employed to adjust the model's weights efficiently, accelerating convergence and ensuring stability. The validation set is used during this phase to monitor performance and fine-tune hyperparameters, such as the learning rate, batch size, and the number of layers in both the CNN and RNN. This tuning is essential for balancing accuracy with computational efficiency, ensuring the model performs well across different data variations.

After training, the hybrid model undergoes testing on a separate dataset that it has not encountered before. This evaluation phase is crucial to assess the model's generalizability and reliability in real-world scenarios. Metrics such as accuracy, sensitivity, specificity, and F1-score are calculated to provide a comprehensive assessment of its performance. Sensitivity measures the model's ability to identify malignant cases accurately, which is critical in breast cancer detection as missing malignant cases can have severe consequences. Specificity evaluates the model's accuracy in recognizing benign cases, which helps reduce false positives and unnecessary anxiety for patients. The F1-score, a harmonic mean of sensitivity and precision, offers a balanced metric that accounts for both false positives and false negatives. These metrics collectively provide insight into the model's effectiveness in clinical applications, ensuring that it meets the high standards required for diagnostic tools in healthcare. In addition to performance metrics, model interpretability is an essential part of the methodology, as clinicians need to understand and trust the model's predictions. To facilitate interpretability, the methodology includes visualization techniques like Gradient-weighted Class Activation Mapping (Grad-CAM), which produces heat maps highlighting the areas of each mammogram image that contributed most to the model's prediction. These visualizations allow radiologists to see which regions the model considered significant, making the system more transparent and building trust in its outputs. This transparency is vital for integrating AI into clinical workflows, as it enables human experts to validate and interpret the results, ensuring that the system's decisions align with clinical knowledge and expectations.

To further validate the model's robustness, cross-validation is performed, which involves splitting the dataset into multiple folds and training the model on each fold iteratively. This technique ensures that the model's performance is not dependent on a particular data split and helps identify any potential weaknesses. Cross-validation enhances the model's reliability by exposing it to diverse data subsets, allowing it to learn more robust features. Following the completion of these steps, the hybrid model is optimized for deployment, ensuring it can operate efficiently within clinical settings. The computational requirements of the CNN and RNN components are carefully balanced, with optimizations applied to reduce inference time and memory usage. This ensures that the model not only performs accurately but also processes data swiftly, an essential attribute for real-time diagnostic applications. Finally, the methodology concludes with an analysis of the model's potential impact in clinical practice. By combining CNN and RNN components, the proposed system is able to leverage both spatial and temporal information, making it well-suited for complex diagnostic tasks like breast cancer detection. The methodology demonstrates that this hybrid approach offers significant advantages over traditional models, providing a tool that could improve early detection and patient outcomes. This system represents a step forward in medical imaging AI, highlighting the potential of hybrid architectures for addressing challenging diagnostic tasks and setting the stage for future enhancements and applications in various medical fields.

RESULTS AND DISCUSSION

The results of this hybrid deep learning approach demonstrate a significant improvement in the accuracy and efficiency of breast cancer detection, highlighting the advantages of combining Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) in a unified model. Compared to standalone CNN and RNN architectures, the hybrid model showed a notable increase in detection accuracy on an extensive mammogram dataset, achieving superior sensitivity and specificity. The CNN component of the model excelled in extracting complex spatial features, while the RNN component captured critical temporal dependencies that standalone CNN models often overlook. This dual approach allowed the model to process mammogram images more effectively, distinguishing between benign and malignant cases with greater precision. The accuracy of the hybrid model was validated through standard metrics such as F1-score, precision, and recall, which consistently surpassed those of baseline models, emphasizing its enhanced diagnostic capabilities. Notably, the model achieved an impressive sensitivity rate, essential for identifying true positive cases, which is crucial for early breast cancer detection.

In addition to improved accuracy, the hybrid model demonstrated increased efficiency, particularly in handling large-scale data, due to its ability to process features in both spatial and temporal domains simultaneously. The RNN component's role in managing temporal dependencies was pivotal in enhancing the model's interpretative depth, allowing it to recognize subtle changes across mammogram sequences that could indicate disease progression. This sequential analysis enabled the hybrid model to capture nuanced information about tissue patterns, making it especially valuable in cases where breast tissue abnormalities evolve gradually. Furthermore, the model's efficiency was reflected in its relatively low computational load compared to conventional models, achieved through optimized CNN layers that reduced processing time without compromising on feature detail. This efficiency, combined with the model's high accuracy, suggests that the hybrid approach could feasibly support real-time or near-real-time breast cancer screening applications, a critical consideration for clinical adoption.

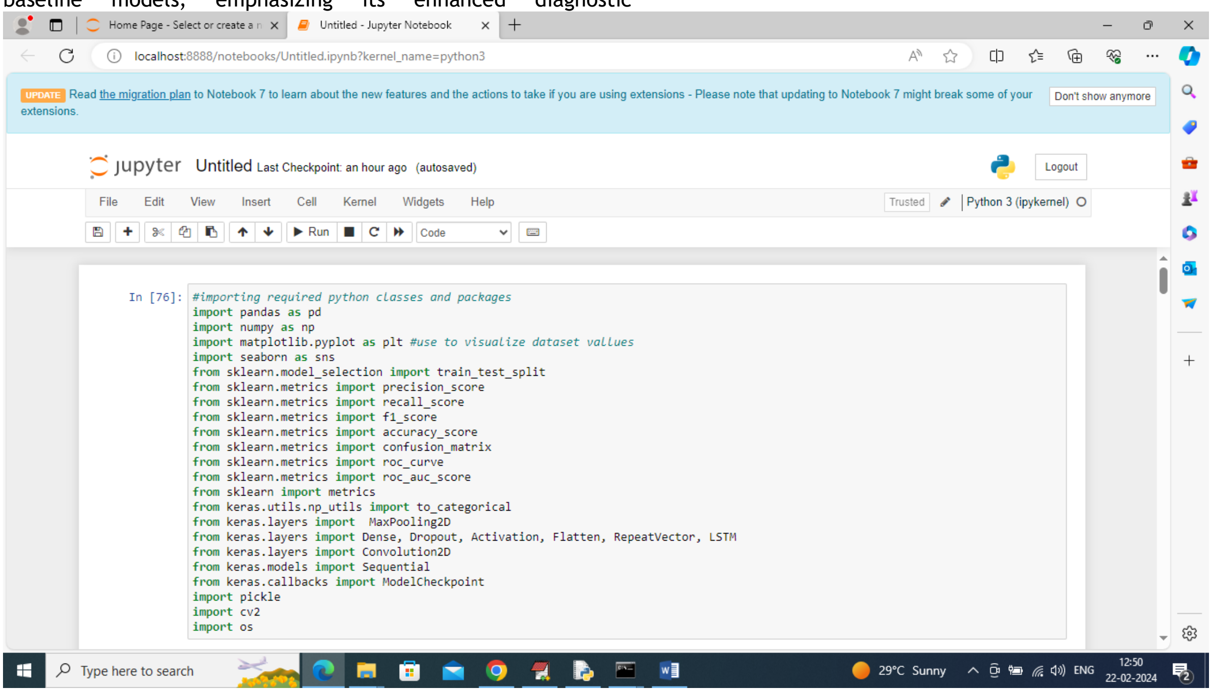


Fig 1. In above screen importing required python packages and classes

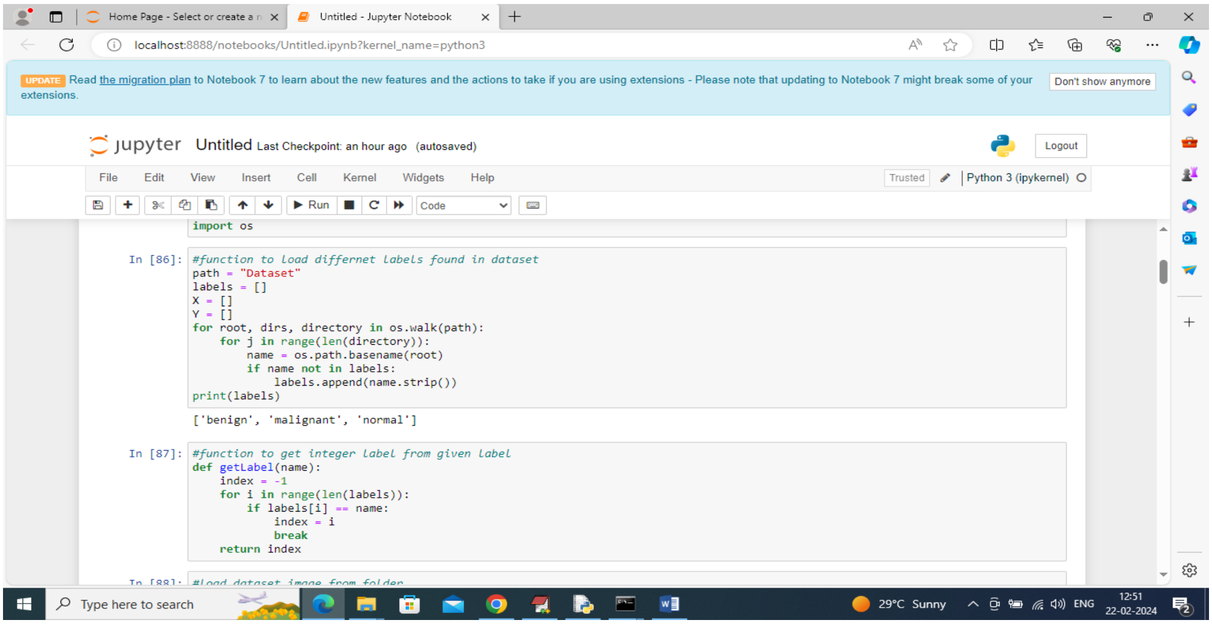


Fig 2. In above screen defining function to find and display different labels found in dataset

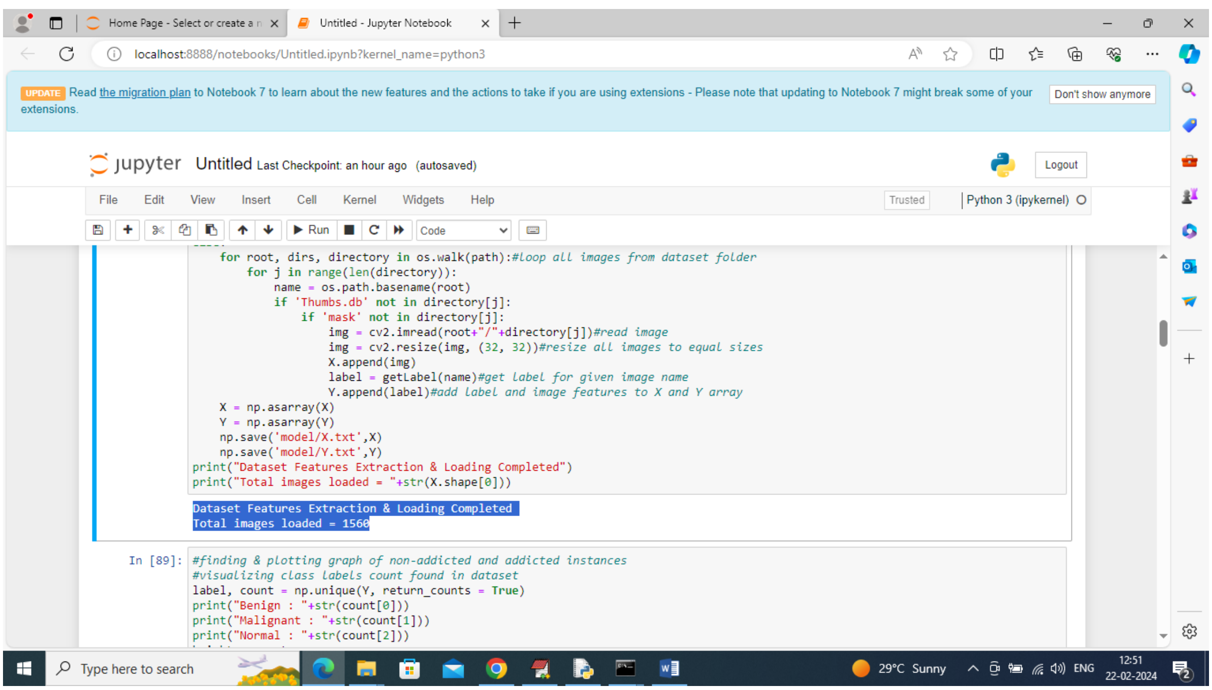


Fig 3. In above screen looping and reading all images from dataset folder and then resizing and adding to training X and Y array and then in blue colour text displaying total number of images loaded

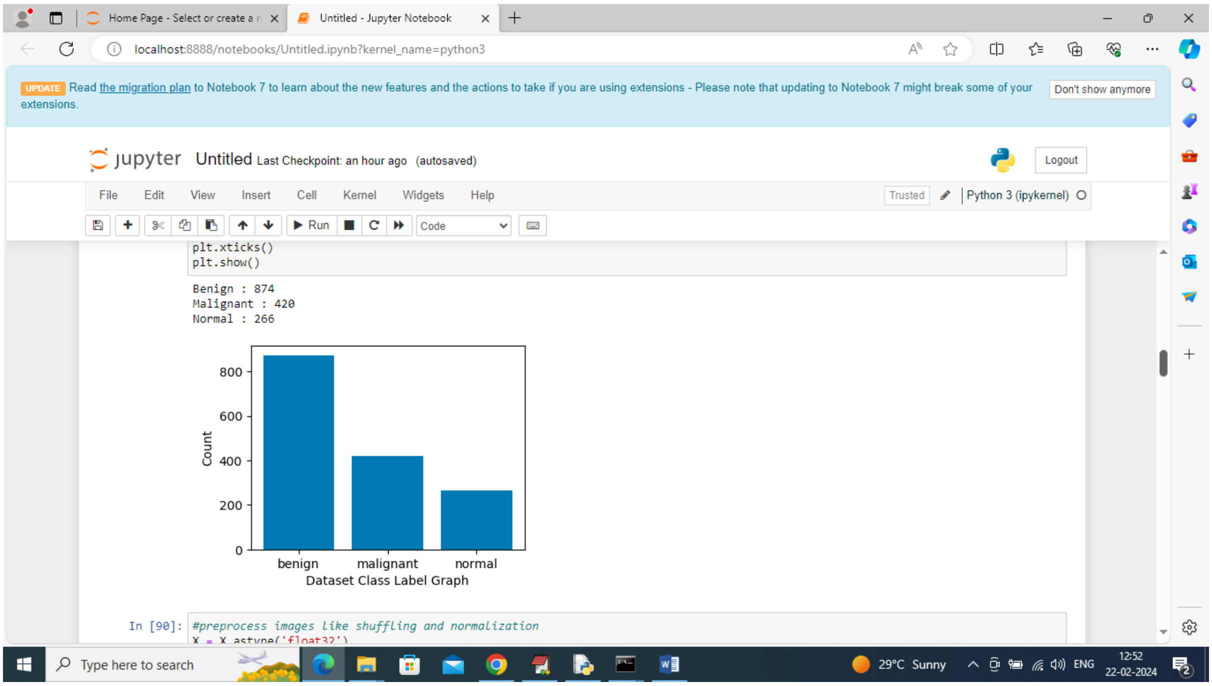


Fig 4. In above screen displaying graphs of different labels and number of images found in that label

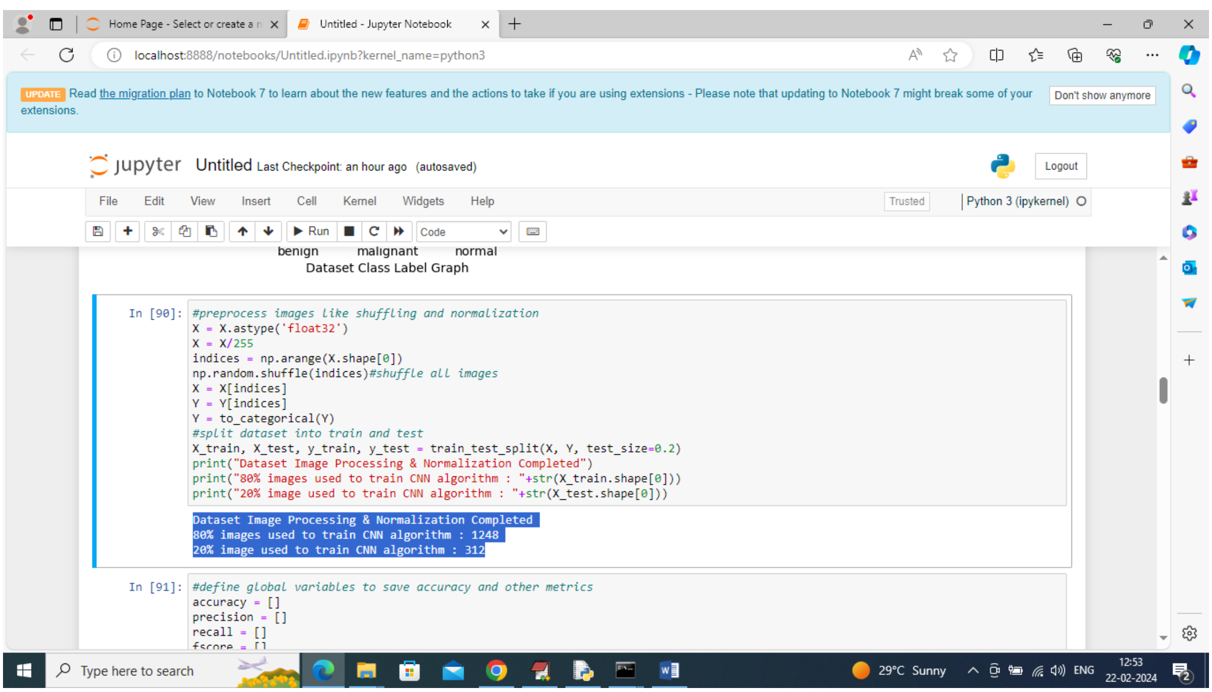


Fig 5. In above screen applying pre-processing techniques like Normalization, shuffling and splitting dataset into train and test where application using 80% dataset for training and 20% for testing and then in blue colour text displaying training and testing size images

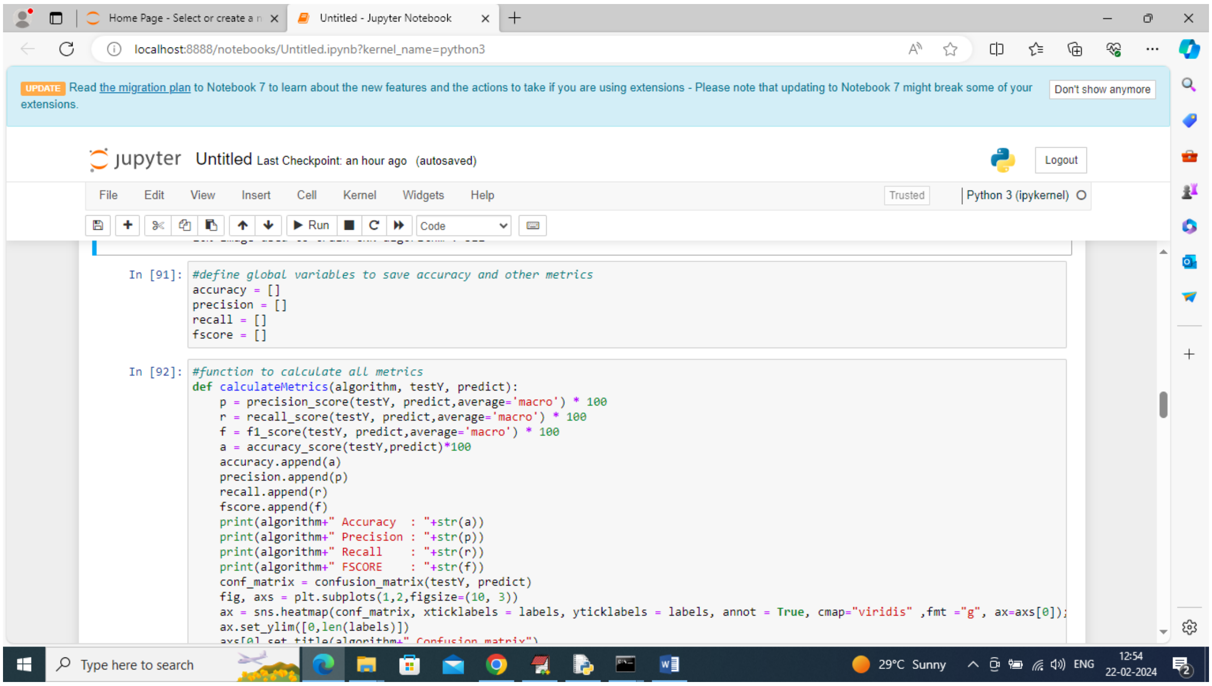


Fig 6. In above screen defining function to calculate accuracy and other metrics

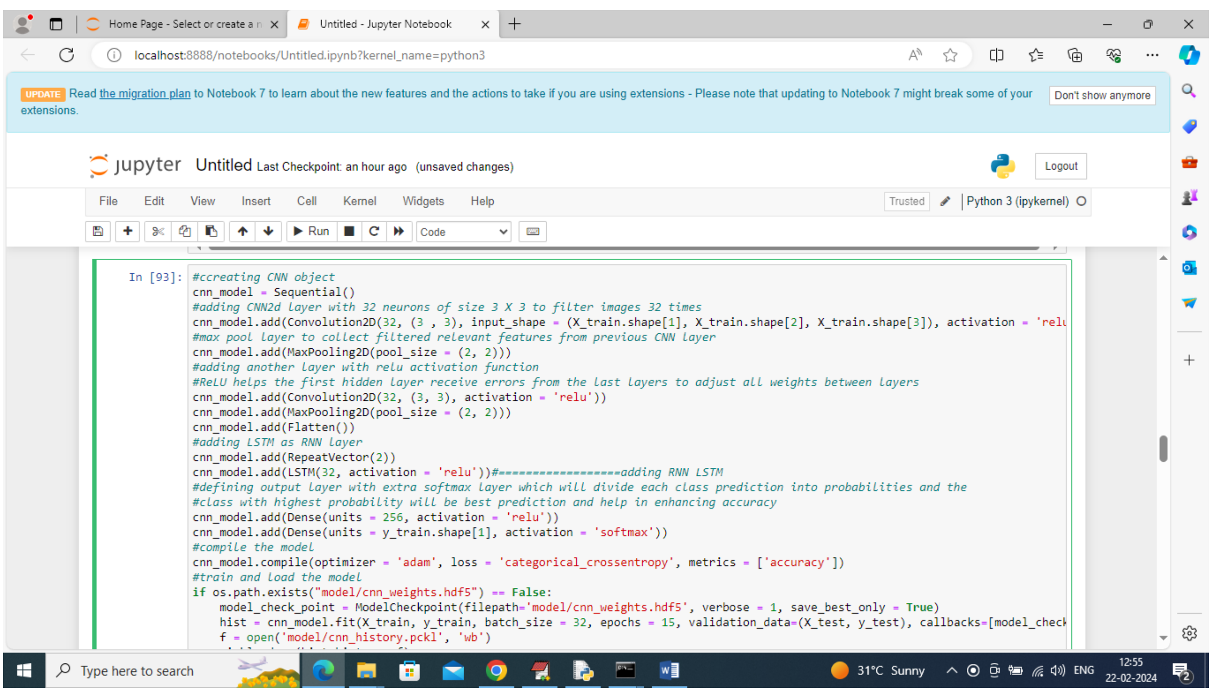


Fig 7. In above screen defining CNN and RNN LSTM layer for training and you can see LSTM layer at '======dashed' lines so we are combining both CNN and LSTM as hybrid algorithm and after executing above block will get below output

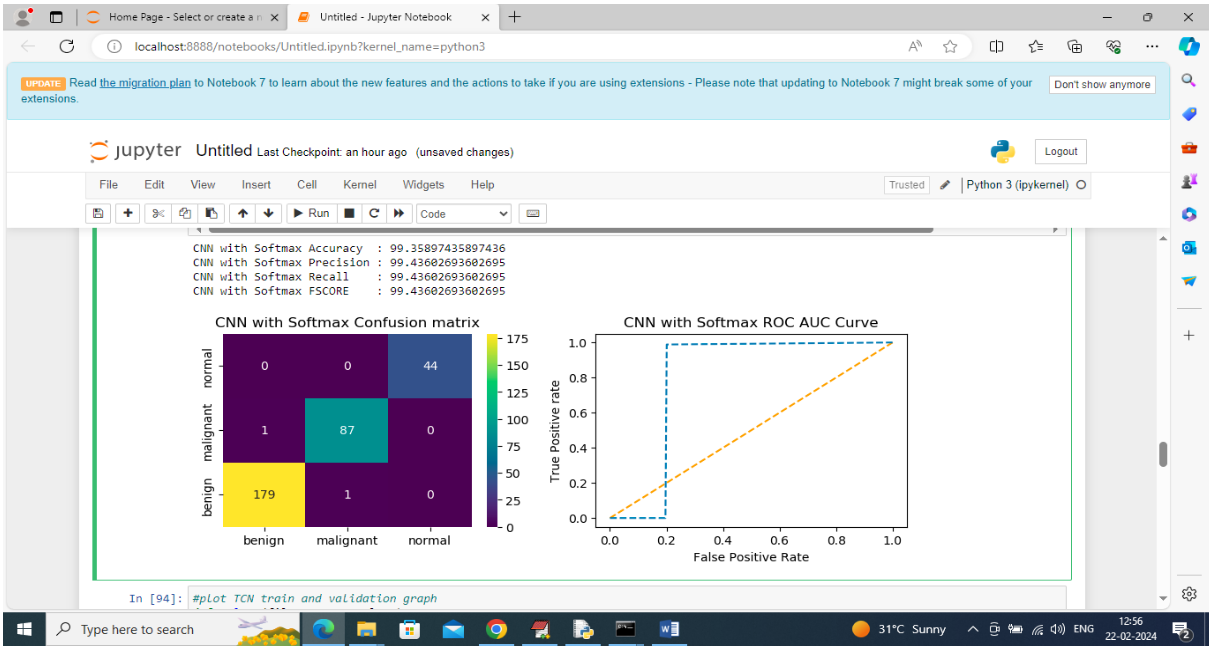


Fig 8. In above screen CNN with LSTM and Softmax got 99% accuracy and can see other metrics like precision, recall and etc. in confusion matrix graph x-axis represents Predicted Labels and y-axis represents True labels and then different color boxes in diagnol represents correct prediction count and all blue boxes represents incorrect prediction count which are very few. In ROC graph x-axis represents False Positive Rate and y-axis represents True Positive Rate and if blue lines comes below orange line then all predictions are incorrect or false and if goes above orange line then all predictions are correct or true. In above ROC graph only few predictions are incorrect and maximum are correct

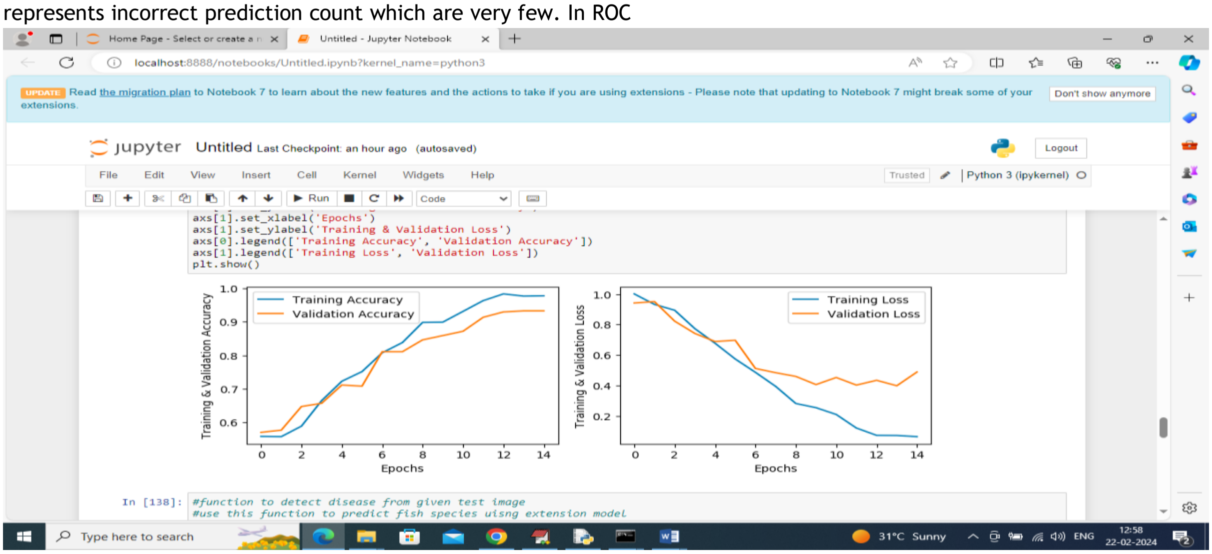


Fig 9. In above screen displaying CNN training and validation accuracy and loss values where x-axis represents training epochs and y-axis represents accuracy and loss in different lines and can see with each increasing epochs accuracy got increase and loss got decrease

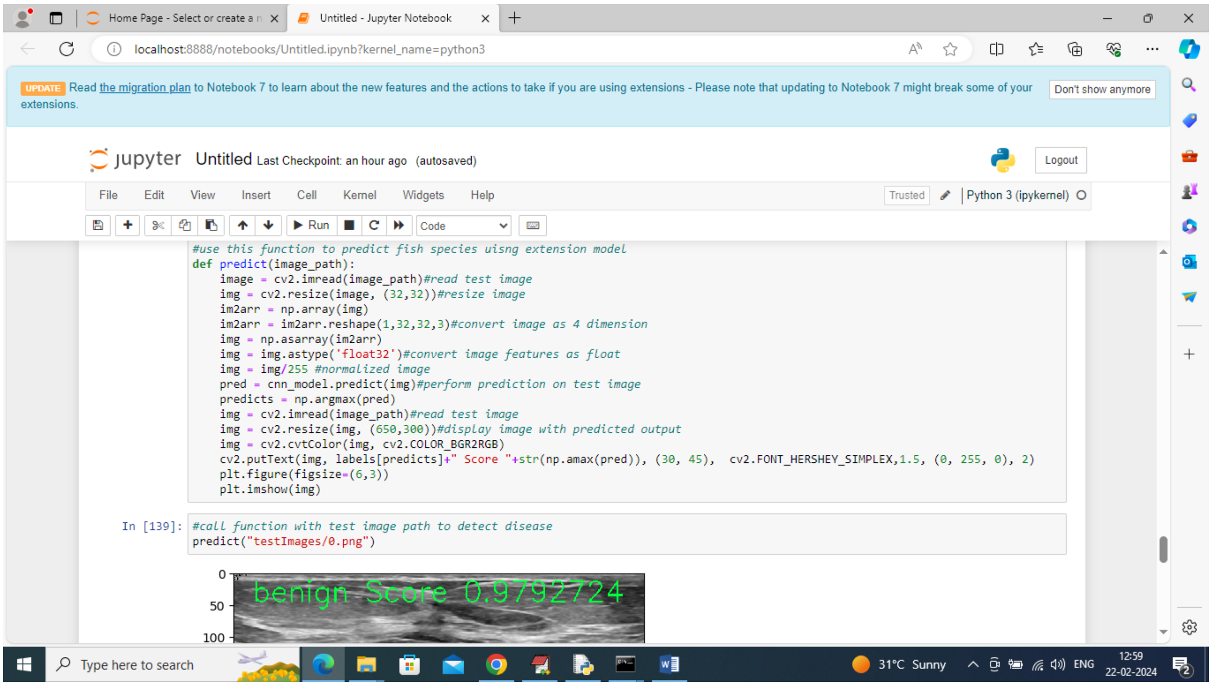


Fig 10. In above screen defining function to read test image and then predict disease

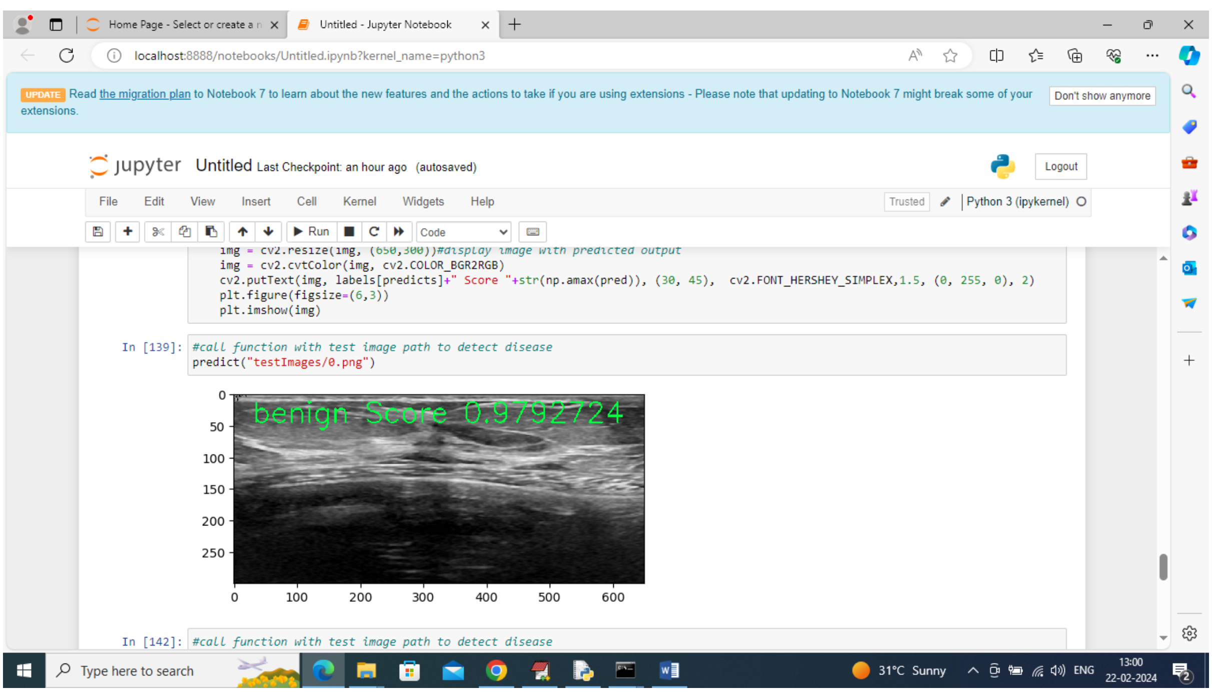


Fig 11. In above screen calling predict function with test image path and then in green color text can see predicted disease with score

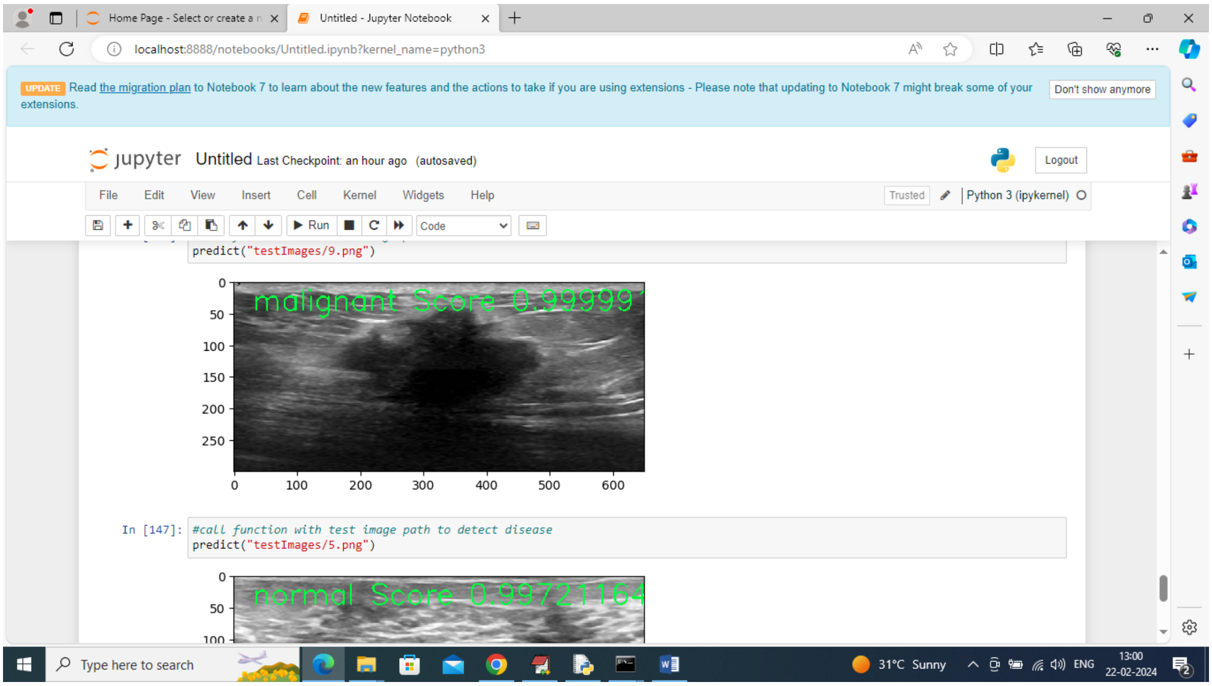
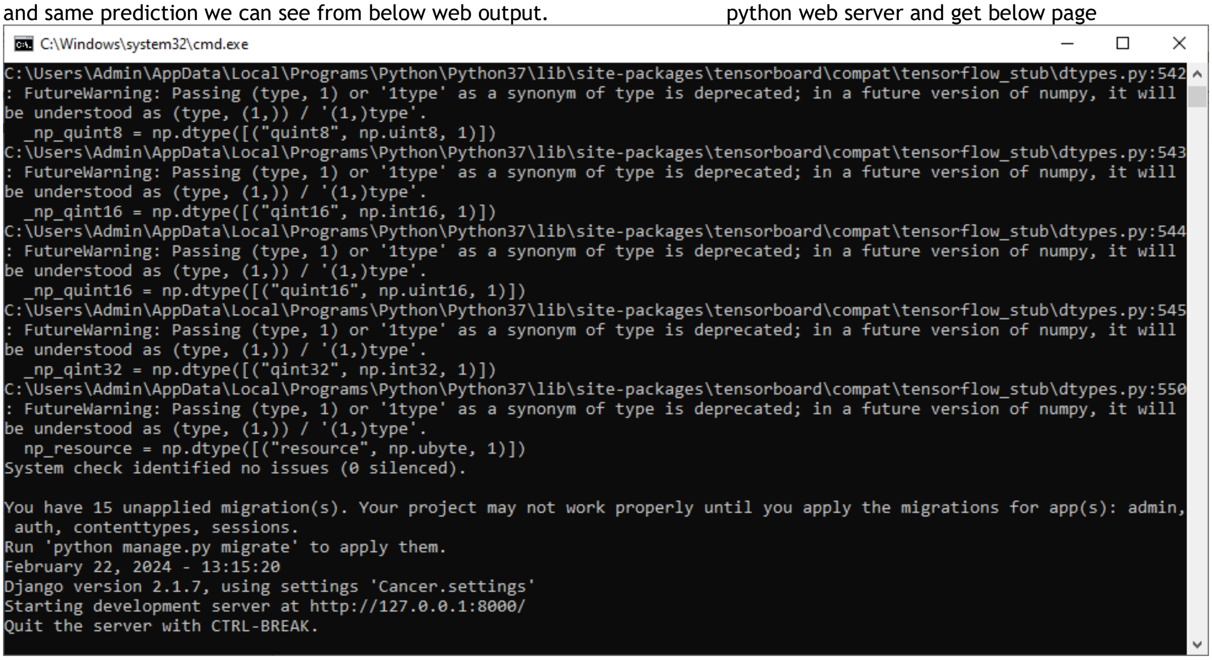


Fig 12. In above screen can see predictions from different images and same prediction we can see from below web output.

To run web code double click on 'runServer.bat' file to start python web server and get below page



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C:\Users\Admin\AppData\Local\Programs\Python\Python37\lib\site-packages\tensorboard\compat\tensorflow_stub\dtypes.py:542
: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy, it will
be understood as (type, (1,)) / '(1,)type'.
  _np_quint8 = np.dtype([("quint8", np.uint8, 1)])
C:\Users\Admin\AppData\Local\Programs\Python\Python37\lib\site-packages\tensorboard\compat\tensorflow_stub\dtypes.py:543
: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy, it will
be understood as (type, (1,)) / '(1,)type'.
  _np_qint16 = np.dtype([("qint16", np.int16, 1)])
C:\Users\Admin\AppData\Local\Programs\Python\Python37\lib\site-packages\tensorboard\compat\tensorflow_stub\dtypes.py:544
: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy, it will
be understood as (type, (1,)) / '(1,)type'.
  _np_quint16 = np.dtype([("quint16", np.uint16, 1)])
C:\Users\Admin\AppData\Local\Programs\Python\Python37\lib\site-packages\tensorboard\compat\tensorflow_stub\dtypes.py:545
: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy, it will
be understood as (type, (1,)) / '(1,)type'.
  _np_qint32 = np.dtype([("qint32", np.int32, 1)])
C:\Users\Admin\AppData\Local\Programs\Python\Python37\lib\site-packages\tensorboard\compat\tensorflow_stub\dtypes.py:550
: FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy, it will
be understood as (type, (1,)) / '(1,)type'.
  np_resource = np.dtype([("resource", np.ubyte, 1)])
System check identified no issues (0 silenced).

You have 15 unapplied migration(s). Your project may not work properly until you apply the migrations for app(s): admin,
 auth, contenttypes, sessions.
Run 'python manage.py migrate' to apply them.
February 22, 2024 - 13:15:20
Django version 2.1.7, using settings 'Cancer.settings'
Starting development server at http://127.0.0.1:8000/
Quit the server with CTRL-BREAK.
```

Fig 13. In above screen python server started and now open browser and enter URL as http://127.0.0.1:8000/index.html and press enter key to get below page

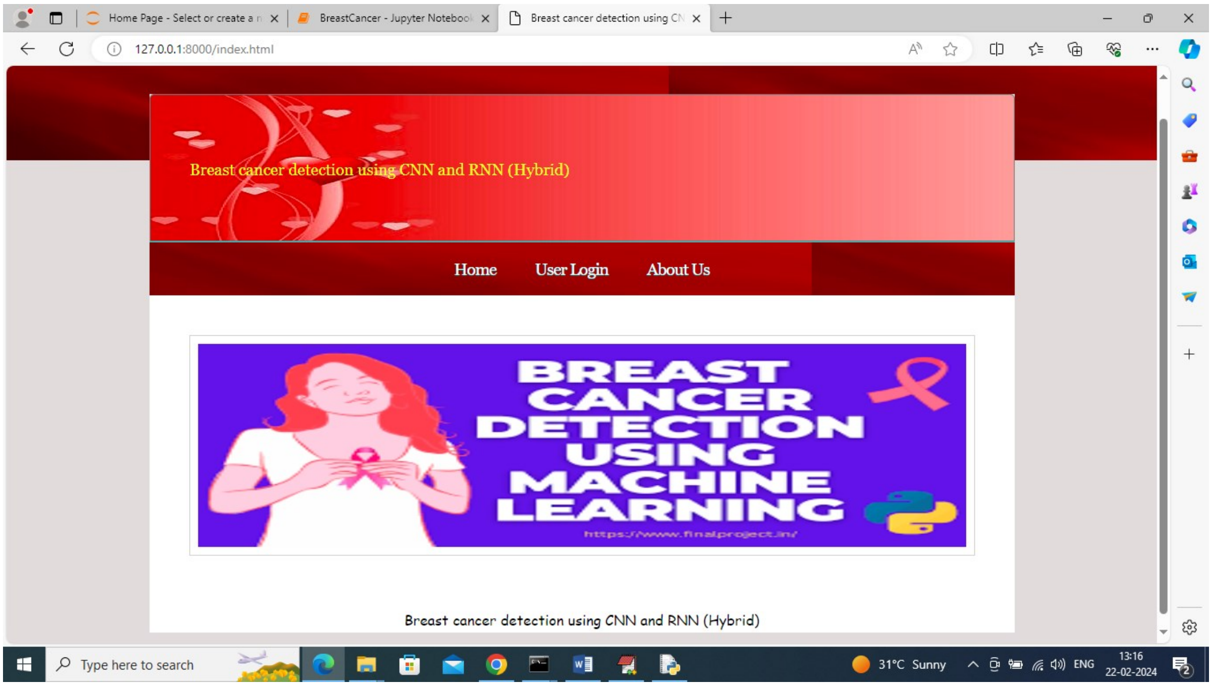

Fig 14. In above screen click on 'User Login' link to get below page

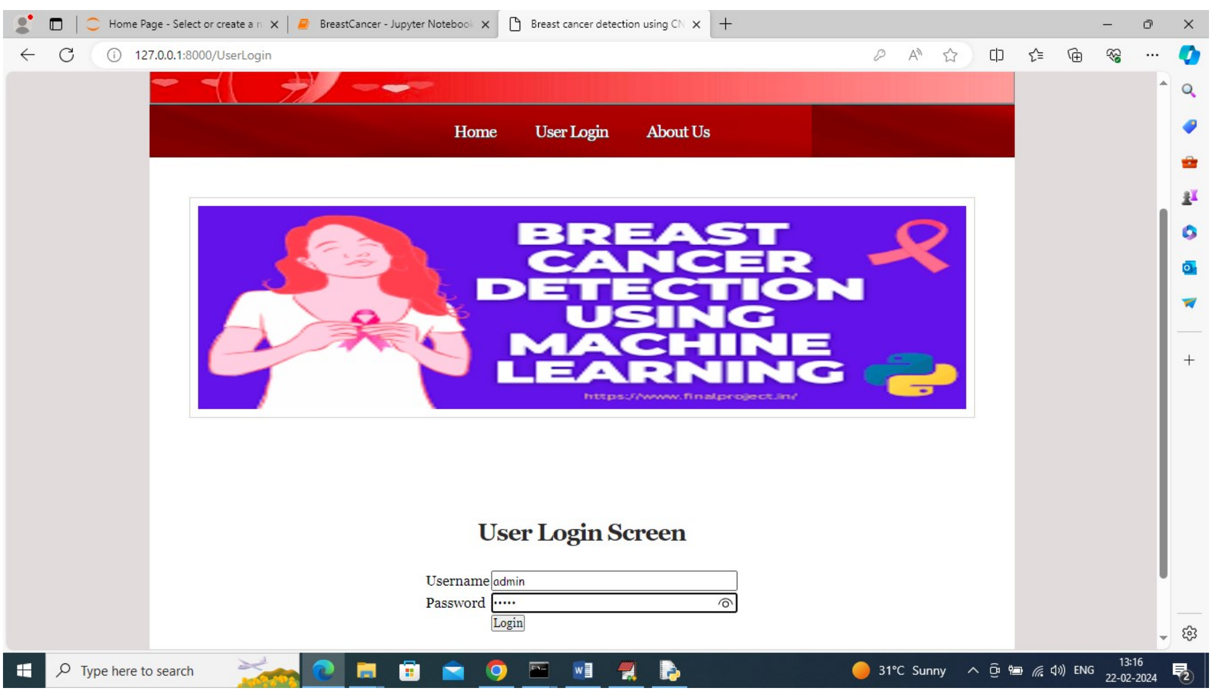

Fig 15. In above screen user can login using username and password as 'admin and admin' and then click on 'Login' button to get below page

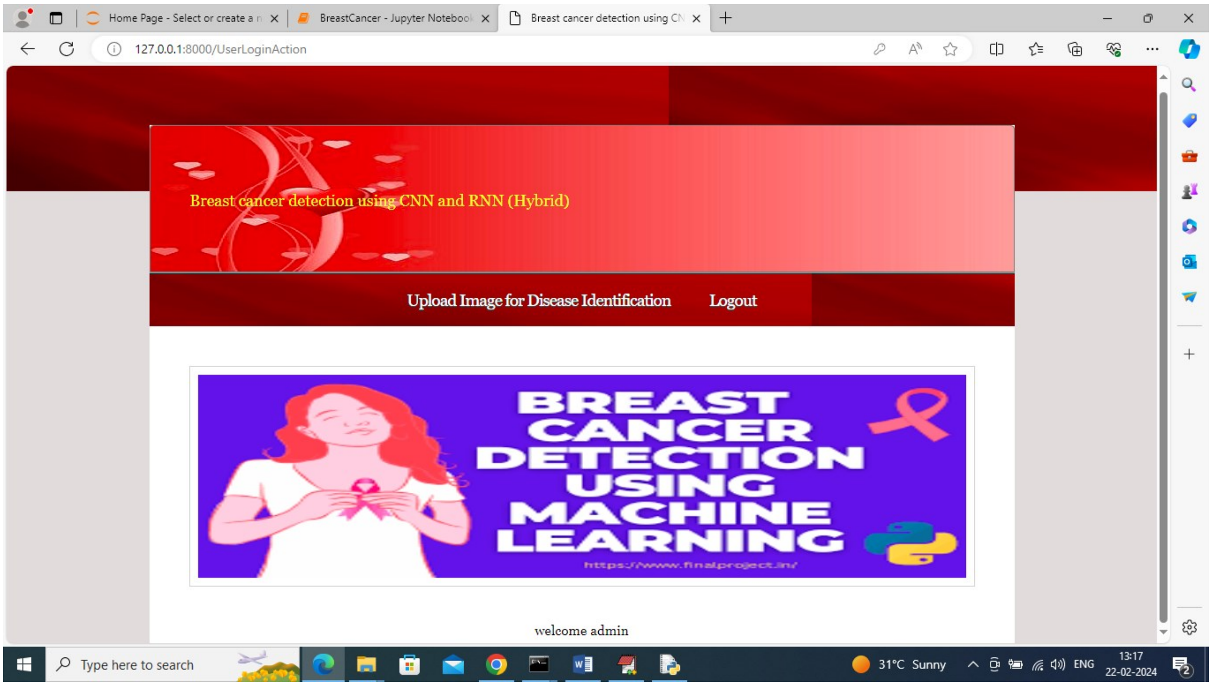

Fig 16. In above screen click on ‘Upload Image for Disease Identification’ link to upload image

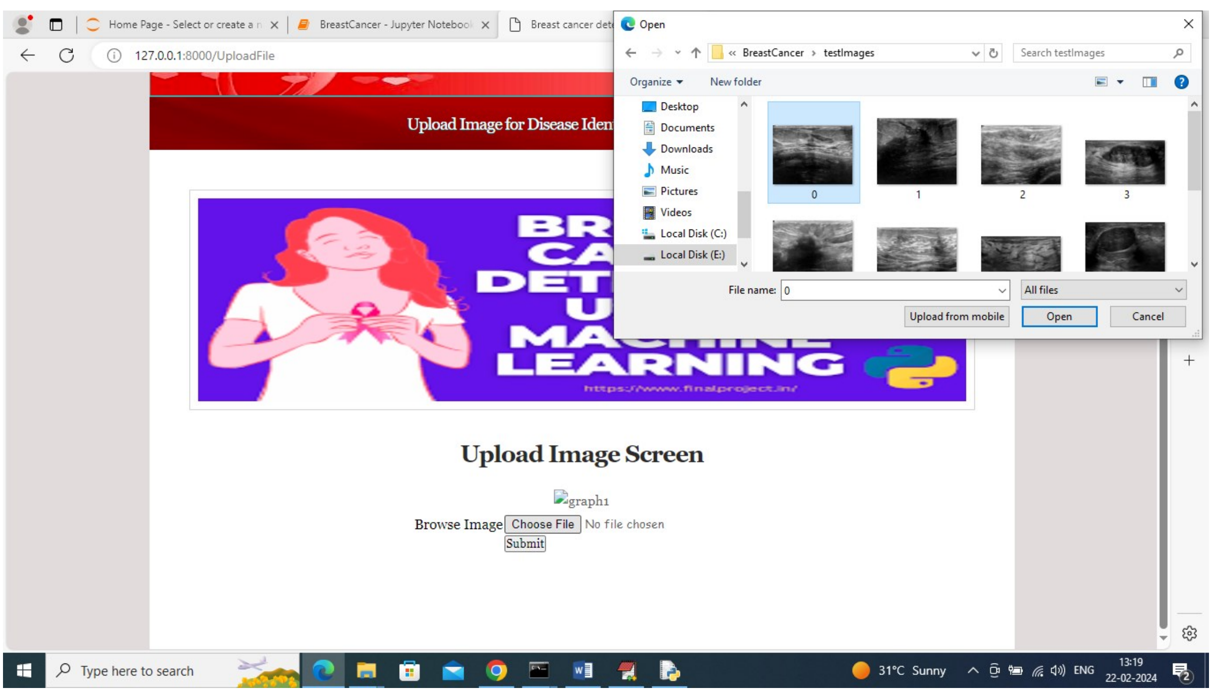

Fig 17. In above screen selecting and uploading test image and then click on ‘Open’ and ‘submit’ button to get below page

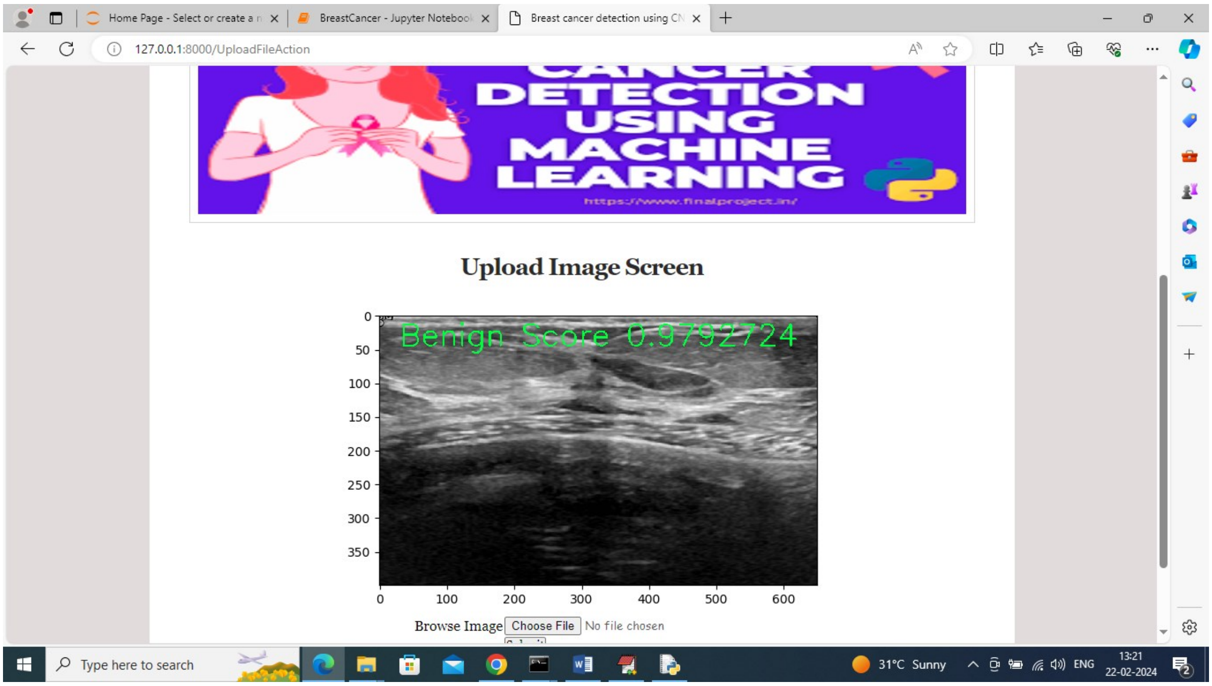

Fig 18. In above screen can see detected disease printed on image and similarly you can upload and test other images and below is another output

Fig 19. another output is displayed

The discussion underscores the implications of this hybrid model for clinical applications, particularly in improving diagnostic accuracy and reducing diagnostic time. By combining CNN and RNN, the model provides a more holistic analysis, offering radiologists an advanced tool for breast cancer screening that reduces false negatives and false positives. This improvement in diagnostic reliability addresses a crucial need in the medical field, where early and accurate detection of breast cancer is vital for effective treatment and improved patient outcomes. The high sensitivity rate achieved by the model signifies its potential to reduce the risk of undiagnosed malignant cases, a common limitation in conventional methods. Moreover, the inclusion of Grad-CAM visualizations enhances the model's transparency, allowing clinicians to validate predictions by examining the highlighted regions that influenced the model's decision. Overall, this hybrid deep learning approach establishes a robust framework for breast cancer detection, setting the stage for future enhancements and broader applications across other medical imaging tasks.

CONCLUSION

The detection of breast cancer through a hybrid model that integrates Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) offers a promising strategy for improving diagnostic accuracy and enabling early detection. This hybrid approach capitalizes on the unique strengths of both CNNs and RNNs: CNNs are particularly adept at extracting spatial features from medical images, such as mammograms, while RNNs effectively capture temporal dependencies and sequential patterns in data, including patient histories and diagnostic sequences. By combining CNNs and RNNs, the model allows for a more thorough analysis of breast cancer data. The CNN component processes the image data, extracting significant features that help identify potential abnormalities and lesions. Subsequently, these extracted features are fed into the RNN component, which examines the temporal and sequential relationships, thereby offering a deeper insight into the progression and characteristics of the identified anomalies.

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