ISSN 2277-2685
IJESR/April-June. 2025/ Vol-15/Issue-2s/141-154
Sagiraju Sai Pavan Kumar Varma *et. al.,* / International Journal of Engineering & Science Research

Breast Cancer Detection Using Cnn And Rnn (Hybrid)

Sagiraju Sai Pavan Kumar Varma, Ch.Jeevan Babu
Pg Scholar, Department Of Mca, Dnr College, Bhimavaram, Andhra Pradesh.
(Assistant Professor), Master Of Computer Applications, Dnr College, Bhimavaram, Andhra Pradesh.

ABSTRACT
Breast cancer forms in breast cells and is considered as a very common type of cancer in women. Breast cancer is also a very life threatening disease of women after lung cancer. A convolutional neural network (CNN) method is proposed in this study to boost the automatic identification of breast cancer by analyzing hostile ductal carcinoma tissue zones in whole-slide images (WSIs). In this paper investigates the proposed system that uses various convolutional neural network (CNN) architectures to automatically detect breast cancer, comparing the results with those from machine learning (ML) algorithms. All architectures were guided by a big dataset of about 275,000, 50 × 50-pixel RGB image patches. Validation tests were done for quantitative results using the performance measures for every methodology. ,e proposed system is found to be successful, achieving results with 87% accuracy, which could reduce human mistakes in the diagnosis process. Moreover, our proposed system achieves accuracy higher than the 78% accuracy of machine learning (ML) algorithms. The proposed system therefore improves accuracy by 9% above results from machine learning (ML) algorithms.
Keywords: Breast Cancer, CNN, RNN.

I. INTRODUCTION

Breast cancer forms in breast cells and is considered as a very common type of cancer in women. Breast cancer is also a very life-threating disease of women after lung cancer. Breast cancer is categorized into various types according to the cell's appearance through a microscopee two main types of breast cancer are (1) invasive ductal carcinoma (IDC) and (2) ductal carcinoma in situ (DCIS), with the latter evolving slowly and, generally, not having negative effects on the daily lives of patients. A low percentage of all cases (between 20% and 53%) are classified as the DCIS type; on the other hand, the IDC type is more dangerous, surrounding the entire breast tissue. Most breast cancer patients, approximately 80%, are in this category [1].

Breast cancer can be effectively treated through its early detection. ,us, the availability of proper screening methods is important for detecting the initial symptom of breast cancer. Various imaging techniques are used for the screening to identify this disease; the popular approaches are mammography, ultrasound, and thermography. One of the most significant methods of early detection for breast cancer is mammography. Ultrasound or diagnostic sonography methods are popularly used as mammography is not effective for solid breasts. Considering these issues, small masses can be bypassed by radiations from radiography and thermography may be more effective than the ultrasound technique in diagnosing smaller cancerous masses [2].

Due to the intrinsic difficulties associated with an image, with meagre contrast, noise, and lack of appreciation by the eye, instruments have been prepared to make and improve image processing. Nowadays, artificial intelligence (AI), machine learning (ML), and convolutional neural network (CNN) are the quickest rising areas of healthcare industry [1, 3–6]. AI and ML are found in the research arena that deals with and improves technological systems to resolve complex tasks through reducing necessity of human intelligence [7–9].

Deep learning (DL) which is part of machine learning family depended on artificial neural networks. DL architectures, such as DNN (deep neural networks), RNN (recurrent neural networks), DBN (deep belief networks), and CNN, are generally applied to the areas like computer vision, audio recognition, speech recognition, social network filtering, natural language processing, machine translation, drug design, bioinformatics, medical image analysis, materials scrutiny, histopathological diagnosis, and board game programs [10–12]. ,ese new technologies, in particular DL algorithms, can be applied to improve the diagnostic accuracy and efficiency of cancer detection [13]. On the other hand, digital pathology (DP) is a way of digitalization of histology slides for producing high-resolution images. ,ese digitized images are used for detection, segmentation, and classification through the application of image analysis techniques.

Extra steps are required in deep learning (DL) using CNNs, such as digital staining, to understand patterns for image classification [14]. ,e opportunity that CNN brings to research on medical imaging is not restricted to deep CNN for extraction of the imaging feature. Indeed, a second field that can support medical research is the use of CNN for synthetic image rendering. Wahab and Khan [15] conducted a study by using MF-CNN (multifaceted fused-CNN) and a hybrid descriptor and revealed that, to assist with mitotic count-based selection of ROIs at lower resolution, acceptable color and textural characteristics are established. ,e MF-CNN recognizes several facets of the input picture to acknowledge dynamic patterns. It includes mitoses, excerpts, and handmade features from ROIs and uses the global image texture to shape a hybrid descriptor to train a classifier assigning WSIs scores.

CNNs are opening up to unimaginable scenarios in areas where it is tedious for domain experts to develop successful features. Gravina et al. [16] noted that the naive use of CNNs might not be successful, since “medical images are more exceptional than normal images.” Mammographic lesion segmentation has been shown to be an effective source of knowledge, as it may help both extract shape-related structures and provide exact lesion localization. An experiment was performed by Tsochatzidis et al. [17] to test the diagnosis of breast cancer with mammograms using CNN. ,ey show that performance assessment in diagnosis is carried out on two datasets of mammographic mass such as DDSM-400 and CBIS-DDSM, with variations in the accuracy of the corresponding segmentation maps of ground truth.

A computer-aided diagnosis (CAD) system was applied by Malathi et al. [18] for mammograms to allow initial identification, examination, and treatment of breast cancer. ,ey discussed exploring a breast CAD architecture focused on characteristic fusion through deep learning of the CNN. ,e result reveals that the RFA (random forest algorithm) has the highest precision with less error than the CNN classifier (95.65 percent). ,e abnormality of the representations of the breast is investigated via the deep belief network (DBN). To discern the abnormal picture, the given work practices activate the contour segmentation and it may be ordered by the DBN.

Desai and Shah [19] mentioned that deep comparison of the operation and architecture of each network is carried out and examination is then conducted based on the precision of the network's diagnosis and categorization of breast malignancy to assess which network outperforms the other. For the diagnosis and identification of breast cancer, CNN is observed to provide somewhat higher precision than MLP. In prior research, Wahab and Khan [15] used CNNs to investigate the automated detection of IDC-type breast cancer. Several scholars used ML-based automatic detection techniques to detect the same. ,is aimed to obtain correct results to lessen the errors found in the diagnosis procedure. ,e study of Abdelhafiz et al. [20] also discovered that augmentation approach was fruitful in the automatic identification of this cancer, when using the given dataset. Another researcher [21] applied deep max pooling CNNs to identify images of mitosis in breast histology. ,e networks were competent to order the images based on pixel.

A DL approach was used by Murtaza et al. [22] for the automatic identification and investigation of IDC tissue zones. Context-aware stacked CNNs were presented by Hossain [4] for the categorization of breast WSIs into simple, DCIS (ductal carcinoma in situ), and IDC (invasive ductal carcinoma). ,e system realized an area beneath the curve of 0.962 for the categorization of malignant and nonmalignant slides and obtained a three-class accurateness of 81.3% for WSI classification, demonstrating its potential for routine diagnostics. ,e works of Alhamid et al. [23] and Qian et al. [24] also presented some techniques to identify them.,eir experiment results showed that the shearlet coefficients' magnitude and phase could enhance detection accuracy and generalizability.

II. LITERATURE SURVEY

[1] M. Masud, A. E. Eldin Rashed, and M. S. Hossain, "Convolutional neural network-based models for diagnosis of breast cancer," Neural Computing and Applications, vol. 5, 2020.

Breast cancer is the most prevailing cancer in the world and each year affecting millions of women. It is also the cause of largest number of deaths in women dying in cancers. During the last few years, researchers are proposing different convolutional neural network models in order to facilitate diagnostic process of breast cancer. Convolutional neural networks are showing promising results to classify cancers using image datasets. There is still a lack of standard models which can claim the best model because of unavailability of large datasets that can be used for models' training and validation. Hence, researchers are now focusing on leveraging the transfer learning approach using pre-trained models as feature extractors that are trained over millions of different images. With this motivation, this paper considers eight different fine-tuned pre-trained models to observe how these models classify breast cancers applying on ultrasound images. We also propose a shallow custom convolutional neural network that outperforms the pre-trained models with respect to different performance metrics. The proposed model shows 100% accuracy and achieves 1.0 AUC score, whereas the best pre-trained model shows 92% accuracy and 0.972 AUC score. In order to avoid biasness, the model is trained using the fivefold cross validation technique. Moreover, the model is faster in training than the pre-trained models and requires a small number of trainable parameters. The Grad-CAM heat map visualization technique also shows how perfectly the proposed model extracts important features to classify breast cancers.

[2] G. Muhammad, M. S. Hossain, and N. Kumar, "EEG-based pathology detection for home health monitoring," IEEE Journal on

Selected Areas in Communications, vol. 39, no. 2, pp. 603–610, 2021.

An electroencephalogram (EEG)-based remote pathology detection system is proposed in this study. The system uses a deep convolutional network consisting of 1D and 2D convolutions. Features from different convolutional layers are fused using a fusion network. Various types of networks are investigated; the types include a multilayer perceptron (MLP) with a varying number of hidden layers, and an autoencoder. Experiments are done using a publicly available EEG signal database that contains two classes: normal and abnormal. The experimental results demonstrate that the proposed system achieves greater than 89% accuracy using the convolutional network followed by the MLP with two hidden layers. The proposed system is also evaluated in a cloud-based framework, and its performance is found to be comparable with the performance obtained using only a local server.

[3] M. Chen, J. Yang, L. Hu, M. S. Hossain, and G. Muhammad, "Urban healthcare big data system based on crowdsourced and cloud-based air quality indicators," IEEE Communications Magazine, vol. 56, no. 11, pp. 14–20, 2018.

The ever accelerating process of globalization enables more than half the population to live in cities. Thus, the air quality in cities exerts critical influence on the health status of more and more urban residents. In this article, based on urban air quality data collected through meteorological sites, mobile crowdsourcing, and IoT sensing, along with users' body signals, we propose an urban healthcare big data system named UH-BigDataSys. In this article, we first introduce a method of integrating multi-source air quality data for the data preparation of artificial-intelligence- based smart urban services. Then a testbed of UH-BigDataSys is set up with the deployment of air-quality-aware healthcare applications. Finally, we provide health guidance for urban residents in aspects of respiratory diseases, outdoor travel, sleep quality, and so on. The ultimate goal of UH-BigDataSys is for urban residents to lead healthier lives.

[4] M. S. Hossain, "Cloud-supported cyber-physical localization framework for patients monitoring," IEEE Systems Journal, vol. 11, no. 1, pp. 118–127, 2017.

The potential of cloud-supported cyber-physical systems (CCPSs) has drawn a great deal of interest from academia and industry. CCPSs facilitate the seamless integration of devices in the physical world (e.g., sensors, cameras, microphones, speakers, and GPS devices) with cyberspace. This enables a range of emerging applications or systems such as patient or health monitoring, which require patient locations to be tracked. These systems integrate a large number of physical devices such as sensors with localization technologies (e.g., GPS and wireless local area networks) to generate, sense, analyze, and share huge quantities of medical and user-location data for complex processing. However, there are a number of challenges regarding these systems in terms of the positioning of patients, ubiquitous access, large-scale computation, and communication. Hence, there is a need for an infrastructure or system that can provide scalability and ubiquity in terms of huge real-time data processing and communications in the cyber or cloud space. To this end, this paper proposes a cloud-supported cyber-physical localization system for patient monitoring using smartphones to acquire voice and electroencephalogram signals in a scalable, real-time, and efficient manner. The proposed approach uses Gaussian mixture modeling for localization and is shown to outperform other similar methods in terms of error estimation.

[5] S. A. Alanazi, M. M. Kamruzzaman, M. Alruwaili, N. Alshammari, S. A. Alqahtani, and A. Karime, "Measuring and preventing COVID-19 using the SIR model and machine learning in smart health care," Journal of Healthcare Engineering, vol. 2020, Article ID 8857346, 12 pages, 2020.

COVID-19 presents an urgent global challenge because of its contagious nature, frequently changing characteristics, and the lack of a vaccine or effective medicines. A model for measuring and preventing the continued spread of COVID-19 is urgently required to provide smart health care services. This requires using advanced intelligent computing such as artificial intelligence, machine learning, deep learning, cognitive computing, cloud computing, fog computing, and edge computing. This paper proposes a model for predicting COVID-19 using the SIR and machine learning for smart health care and the well-being of the citizens of KSA. Knowing the number of susceptible, infected, and recovered cases each day is critical for mathematical modeling to be able to identify the behavioral effects of the pandemic. It forecasts the situation for the upcoming 700 days. The proposed system predicts whether COVID-19 will spread in the population or die out in the long run. Mathematical analysis and simulation results are presented here as a means to forecast the progress of the outbreak and its possible end for three types of scenarios: "no actions," "lockdown," and "new medicines." The effect of interventions like lockdown and new medicines is compared with the "no actions" scenario. The lockdown case delays the peak point by decreasing the infection and affects the area equality rule of the infected curves. On the other side, new medicines have a significant impact on infected curve by decreasing the number of infected people about time. Available forecast data on COVID-19 using simulations predict that the highest level of cases might occur between 15 and 30 November 2020. Simulation data suggest that the virus might be fully under control only after June 2021. The reproductive rate shows that measures such as government lockdowns and isolation of individuals are not enough to stop the pandemic. This study recommends that authorities should, as soon as possible, apply a strict long-term containment strategy to reduce the epidemic size successfully.

[6] Y. Zhang, X. Ma, J. Zhang, M. S. Hossain, G. Muhammad, and S. U. Amin, "Edge intelligence in the cognitive internet of things: improving sensitivity and interactivity," IEEE Network, vol. 33, no. 3, pp. 58–64, 2019.

A new network paradigm, CIoT, has been proposed by applying cognitive computing technologies, which is derived from cognitive science and artificial intelligence in combination with the data generated by connected IoT devices and the actions that these devices perform. The development of cognitive computing is very important in the above process to meet key technical challenges, such as generation of big sensory data, efficient computing/storage at the CIoT edge, and integration of multiple data sources and types. On the other hand, to evolve with the new computing and communication paradigms, the CIoT ecosystem has to update by absorbing new capabilities such as deep learning, the CIoT sensing system, data analytics, and cognitiion in providing human-like intelligence

[7] M. M. Kamruzzaman, "Architecture of smart health care system using artificial intelligence," in Proceedings of the 2020 IEEE International Conference on Multimedia &

Expo Workshops (ICMEW), pp. 1–6, London, UK, July 2020.

Artificial intelligence is becoming increasingly useful for doctors, nurses, radiologists, researchers, pharmacists, emergency medical service, and many other healthcare professionals. This paper proposes the creation of a smart healthcare system using artificial intelligence as a means of efficiently solving challenges in the healthcare industry and as a tool for optimizing patient care plans. The proposed AI-assisted system shows that it can support a patient who is admitted to the hospital through emergency medical services, easily process the patient's data, and offer early detection of serious diseases. It can automatically recognize the complicated patterns which have been obtained from radiologists, can analyze complete human molecular data and genetics in the clinic, and can support doctors by producing AI-generated radiologist reports, clinical laboratory reports, and many other decision-support tools. The proposed architecture can easily handle diverse and complicated healthcare problems and can be used by any modern hospital to save time and money. This work also shows the recent development of AI applications in healthcare, which could be used in the proposed architecture.

III. PROPOSED METHOD

As per your instruction we have developed combination of CNN & LSTM (RNN) to detect breast cancer disease and as an extra layer we have added RELU with Softmax. ReLU helps the first hidden layer receive errors from the last layers to adjust all weights between layers and Softmax layer which will divide each class prediction into probabilities and the class with highest probability will be best prediction and help in enhancing accuracy.

Proposing a methodology for breast cancer detection using a hybrid CNN and RNN approach involves several key steps, including data preprocessing, model architecture design, training, and evaluation. Here's a proposed methodology:

Data Collection and Pre-processing:

- Gather a diverse dataset comprising medical images (such as mammograms, MRIs, or ultrasounds) and sequential data (such as patient demographics, genetic profiles, or longitudinal health records).
- Preprocess the medical images by standardizing pixel intensities, resizing images to a uniform resolution, and augmenting the dataset to increase variability and robustness.
- Process sequential data by encoding categorical variables, normalizing numerical features, and handling missing values appropriately.

Model Architecture Design:

- Design a hybrid CNN-RNN architecture that integrates convolutional layers for image feature extraction and recurrent layers for sequential data processing.
- Stack convolutional layers to form the CNN component, followed by pooling layers for downsampling and feature aggregation.
- Integrate recurrent layers (such as Long Short-Term Memory, or LSTM, cells) to process sequential data, capturing temporal dependencies and patterns.
- Concatenate or merge the outputs from both CNN and RNN components to combine image-based and sequential features.
- Add fully connected layers and activation functions to the model architecture for classification purposes, followed by a softmax layer for probability estimation.

ISSN 2277-2685
IJESR/April-June. 2025/ Vol-15/Issue-2s/141-154

Model Training:

- Split the dataset into training, validation, and test sets using appropriate ratios (e.g., 70% training, 15% validation, 15% test).
- Train the hybrid CNN-RNN model using a suitable optimization algorithm (e.g., Adam, RMSprop) and a binary cross-entropy loss function.
- Utilize techniques such as batch normalization, dropout, and early stopping to prevent overfitting and improve generalization.
- Fine-tune hyperparameters (e.g., learning rate, batch size, number of epochs) through grid search or random search on the validation set.

Model Evaluation:

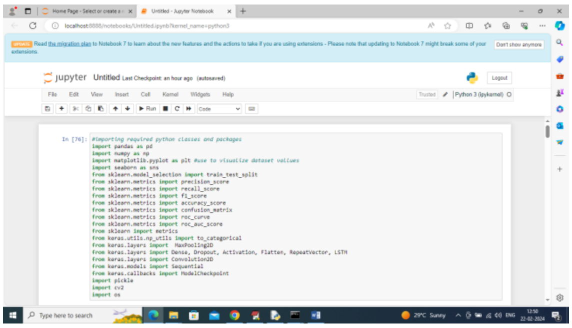
- Evaluate the trained model's performance on the held-out test set using relevant metrics such as accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC).
- Analyze the model's predictions and misclassifications to identify potential areas for improvement and refine the methodology.
- Perform additional experiments to assess the model's robustness to variations in data distribution, imaging modalities, and patient characteristics.
- Compare the performance of the hybrid CNN-RNN model with baseline models or single-modality approaches to demonstrate its superiority in breast cancer detection tasks.

Deployment and Validation:

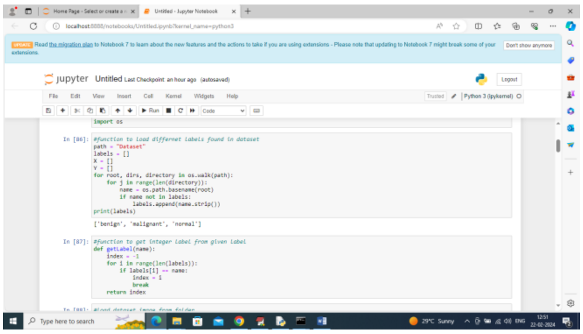
- Deploy the trained model in a clinical setting or research environment for real-world testing and validation.
- Collaborate with domain experts, radiologists, and healthcare professionals to validate the model's efficacy, interpretability, and clinical utility.
- Monitor the model's performance over time and update it periodically with new data or advancements in technology to ensure continued effectiveness and relevance.

IV. RESULTS ANALYSIS

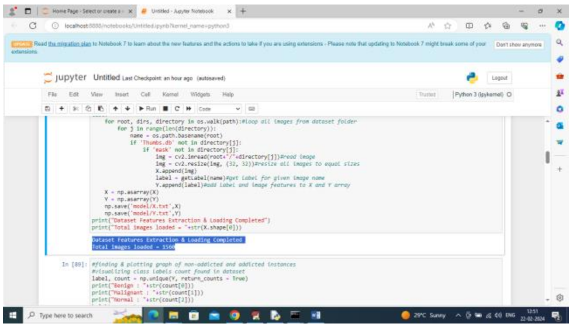
To train above algorithms we have utilized same dataset given by your and we have coded this project using JUPYTER notebook and below are the code and output screens with blue colour comments. All processing and model training we done using JUPYTER and disease prediction will be running from WEB.



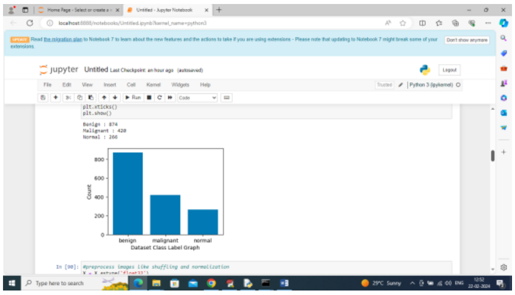
In above screen importing required python packages and classes



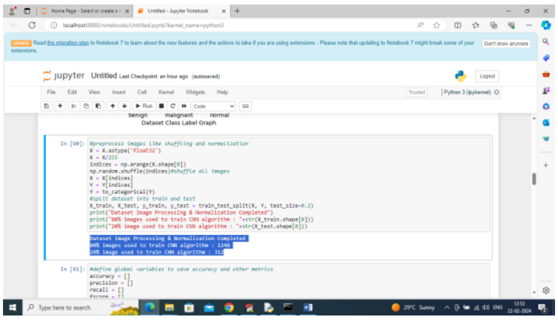
In above screen defining function to find and display different labels found in dataset



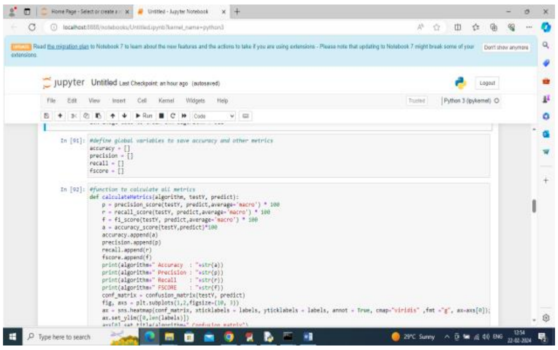
In above screen looping and reading all images from dataset folder and then resizing and adding to training X and Y array and then in blue colour text displaying total number of images loaded



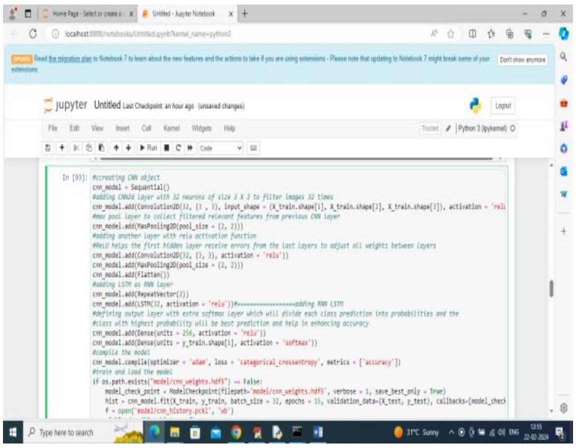
In above screen displaying graphs of different labels and number of images found in that label



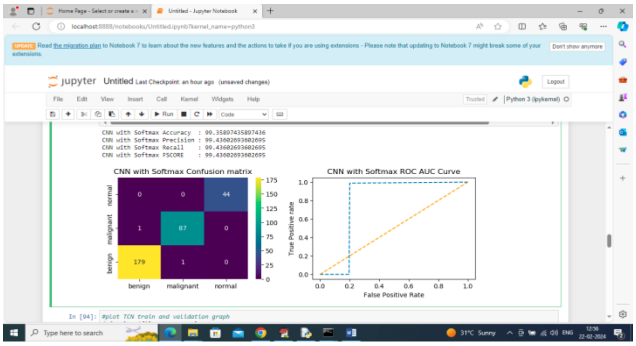
In above screen applying pre-processing techniques like Normalization, shuffling and splitting dataset into train and test where application using 80% dataset for training and 20% for testing and then in blue colour text displaying training and testing size images



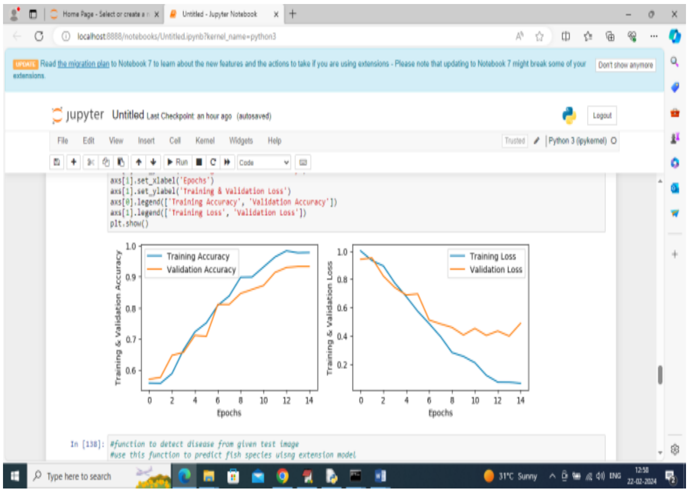
In above screen defining function to calculate accuracy and other metrics



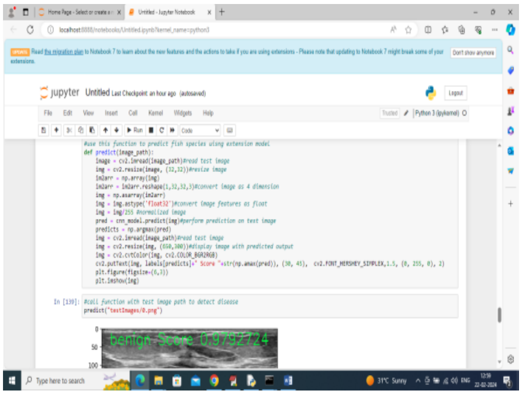
In above screen defining CNN and RNN LSTM layer for training and you can see LSTM layer at '======dashed' lines so we are combining both CNN and LSTM as hybrid algorithm and after executing above block will get below output



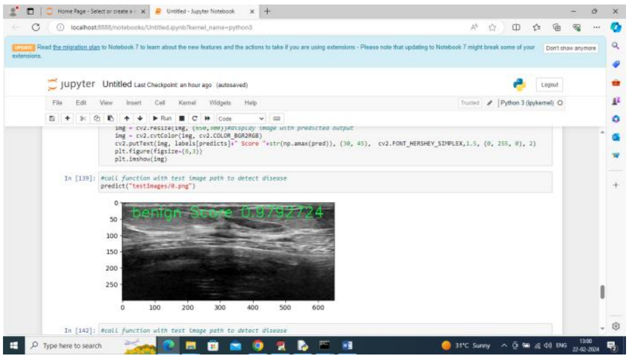
In above screen CNN with LSTM and Softmax got 99% accuracy and can see other metrics like precision, recall and etc. in confusion matrix graph x-axis represents Predicted Labels and y-axis represents True labels and then different color boxes in diagnol represents correct prediction count and all blue 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



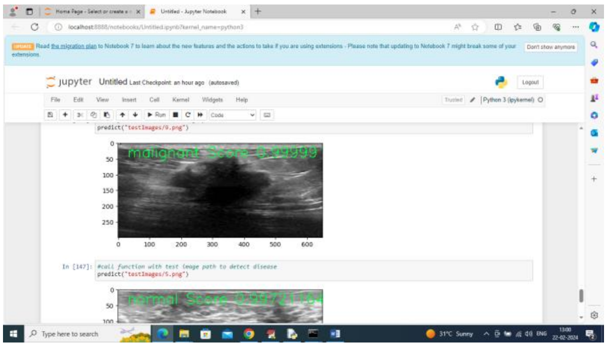
In above screen displaying CNN training and validation accuracy and loss values where x-axis represents training epochs and y-axis represents accuracy and loss in different lines and can see with each increasing epochs accuracy got increase and loss got decrease



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

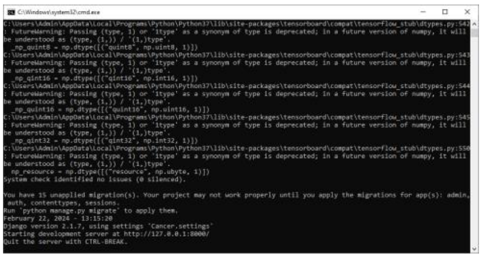


In above screen calling predict function with test image path and then in green color text can see predicted disease with score

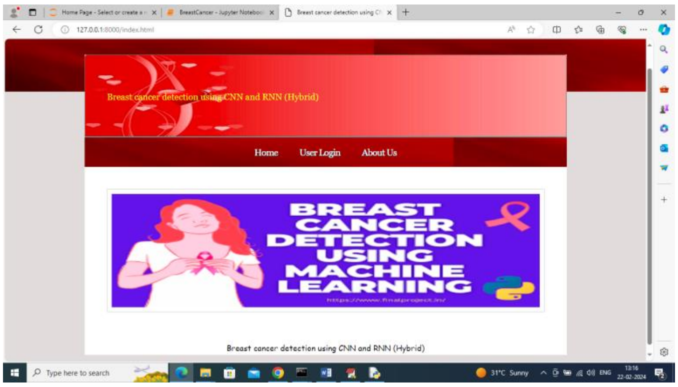


In above screen can see predictions from different images and same prediction we can see from below web output.

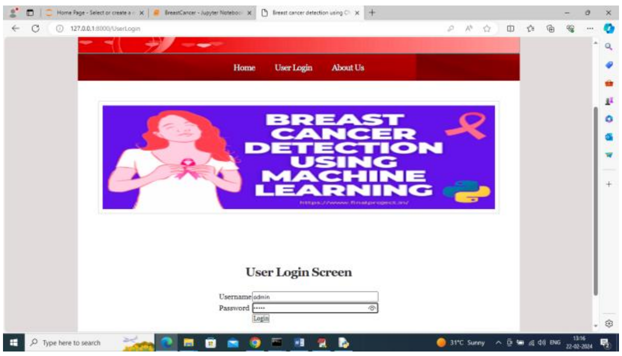
To run web code double click on 'runServer.bat' file to start python web server and get below page



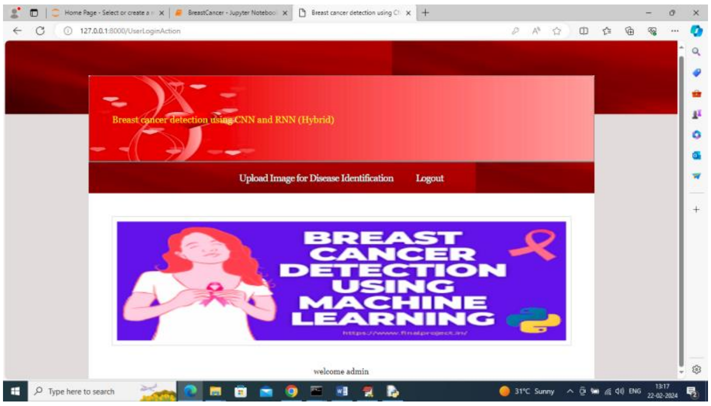
In above screen python server started and now open browser and enter URL as http://127.0.0.1:8000/index.html and press enter key to get below page



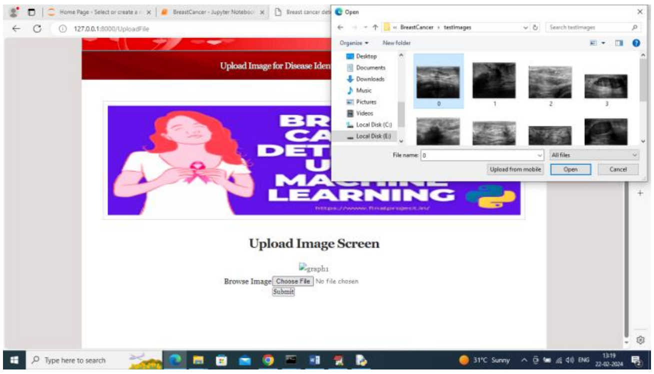
In above screen click on 'User Login' link to get below page



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

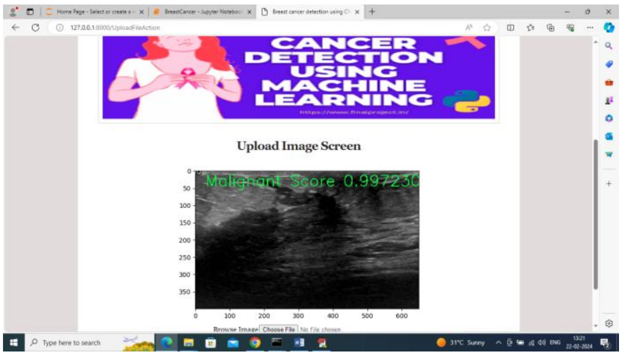


In above screen click on ‘Upload Image for Disease Identification’ link to upload image



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

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



V. CONCLUSION

Automating the detection of breast cancer to enhance the care of patients is a challenging task. ,e current study proposes a CNN approach that analyzes the IDC tissue regions in WSIs for the automatic detection of this cancer. ,ree different CNN architectures have been described in this paper with a proper comparison. ,e proposed system using CNN Model 3 achieves 87% accuracy. Although Model 3 is deeper than Models 1 and 2, the five-layer CNN in Model 3 is best suited for this task. All architectures were guided by a big dataset of about 275,000, 50 × 50-pixel RGB image patches. When we compared the proposed model with the machine learning (ML) algorithm, the proposed model improved accuracy by 8% over the result of the algorithm. ,e proposed model was found to successfully obtain correct results that might decrease human mistakes in the diagnosis process and reduce the cost of cancer diagnosis. ,e main limitation of this study is to use the secondary database like Kaggle, and future study should be done based on primary data for more accuracy of the results related to breast cancer identification.

REFERENCES

[1] M. Masud, A. E. Eldin Rashed, and M. S. Hossain, “Convolutional neural network-based models for diagnosis of breast cancer,” Neural Computing and Applications, vol. 5, 2020.

[2] G. Muhammad, M. S. Hossain, and N. Kumar, “EEG-based pathology detection for home health monitoring,” IEEE Journal on Selected Areas in Communications, vol. 39, no. 2, pp. 603–610, 2021.

[3] M. Chen, J. Yang, L. Hu, M. S. Hossain, and G. Muhammad, “Urban healthcare big data system based on crowdsourced and cloud-based air quality indicators,” IEEE Communications Magazine, vol. 56, no. 11, pp. 14–20, 2018.

[4] M. S. Hossain, “Cloud-supported cyber-physical localization framework for patients monitoring,” IEEE Systems Journal, vol. 11, no. 1, pp. 118–127, 2017.

[5] S. A. Alanazi, M. M. Kamruzzaman, M. Alruwaili, N. Alshammari, S. A. Alqahtani, and A. Karime, “Measuring and preventing COVID-19 using the SIR model and machine learning in smart health care,” Journal of Healthcare Engineering, vol. 2020, Article ID 8857346, 12 pages, 2020.

[6] Y. Zhang, X. Ma, J. Zhang, M. S. Hossain, G. Muhammad, and S. U. Amin, “Edge intelligence in the cognitive internet of things: improving sensitivity and interactivity,” IEEE Network, vol. 33, no. 3, pp. 58–64, 2019.

[7] M. M. Kamruzzaman, “Architecture of smart health care system using artificial intelligence,” in Proceedings of the 2020 IEEE International Conference on Multimedia & Expo Workshops (ICMEW), pp. 1–6, London, UK, July 2020.

[8] W. Min, B.-K. Bao, C. Xu, and M. S. Hossain, “Cross-platform multi-modal topic modeling for personalized inter-platform recommendation,” IEEE Transactions on Multimedia, vol. 17, no. 10, pp. 1787–1801, 2015.

[9] M. M. Kamruzzaman, “Arabic sign language recognition and generating Arabic speech using convolutional neural network,” Wireless Communications and Mobile Computing, vol. 2020, Article ID 3685614, 9 pages, 2020.

[10] M. S. Hossain, S. U. Amin, M. Alsulaiman, and G. Muhammad, “Applying deep learning for epilepsy seizure detection and brain mapping visualization,” ACM Transactions on Multimedia Computing, Communications, and Applications, vol. 15, no. 1, pp. 1–17, 2019.

[11] J. L. Wang, A. K. Ibrahim, H. Zhuang, A. Muhamed Ali, A. Y. Li, and A. Wu, "A study on automatic detection of IDC breast cancer with convolutional neural networks," in Proceedings of the 2018 International Conference on Computational Science and Computational Intelligence (CSCI), pp. 703–708, Las Vegas, NV, USA, December 2018.

[12] M. S. Hossain and G. Muhammad, "Emotion-aware connected healthcare big data towards 5G," IEEE Internet of @ings Journal, vol. 5, no. 4, pp. 2399–2406, 2018.

[13] A. Cruz-Roa, A. Basavanhally, F. Gonzalez et al., "Automatic ´ detection of invasive ductal carcinoma in whole slide images with convolutional neural networks," Medical Imaging 2014: Digital Pathology, vol. 9041, no. 216, p. 904103, 2014.

[14] S. U. Amin, M. Alsulaiman, G. Muhammad, M. A. Bencherif, and M. S. Hossain, "Multilevel weighted feature fusion using convolutional neural networks for EEG motor imagery classification," IEEE Access, vol. 7, pp. 18940–18950, 2019.

[15] N. Wahab and A. Khan, "Multifaceted fused-CNN based scoring of breast cancer whole-slide histopathology images," Applied Soft Computing, vol. 97, p. 106808, 2020.