



# BREAST CANCER DETECTION BASED ON CONVOLUTIONAL NEURAL NETWORKS

<sup>1</sup>Ms.Sharon J Christina, <sup>2</sup>Deeksha C P, <sup>3</sup>Teja N L, <sup>4</sup>Gunashree B, <sup>5</sup>Divya V

<sup>1</sup>Professor, <sup>2</sup>Student, <sup>3</sup>Student, <sup>4</sup>Student, <sup>5</sup>Student

Computer Science and Engineering,

Cambridge Institute of Technology, Bangalore, India

*Abstract:* The most common kind of cancer in women, breast cancer is bad for both physical and emotional health in those who have it.. Breast cancer remains a significant health concern worldwide, with early detection crucial for successful treatment. Due to complexities present in Breast Cancer images, image processing technique is required for detecting cancer. New deep learning techniques were needed for early breast cancer detection. Histopathological pictures are used as the dataset for this research. Breast tissue histopathological investigation is essential for the diagnosis of breast cancer. This project aims to develop a web application using Django, a Python-based web framework, for managing and viewing breast cancer histopathological images. Images are processed using histogram normalization techniques. This project implements the Convolutional Neural Network (CNN) model based on deep learning and helps in improving the efficiency of breast cancer diagnosis.

**Index Terms** – Early Detection, Deep learning, Histopathological Images, CNN Algorithm, Image Processing.

## I. INTRODUCTION

The cancer that is most common in women worldwide is breast cancer, and a key component of the diagnosis of this disease is histopathological investigation. Breast Biopsy is the most precise solution where a sample piece of tissue is taken for the microscopic examination. This study of biological tissues under the microscope is called histopathology. An expert doctor is required to examine the histopathological images and it is a time-consuming process. However, managing and accessing histopathological images can be challenging because of the volume and complexity of data. This project aims at solving this issue by developing a web application that streamlines the easy retrieval of breast cancer histopathological images. The computer-assisted diagnosis (CAD) is used for classifying malignant and benign cancer from images. This study focuses on classifying histopathological images using deep learning and transfer learning techniques. The use of Deep learning will reduce the load from the radiologist and they can more concentrate on only suspicious cases.

## II. OBJECTIVE

This project utilized the CNN method and the Histopathological dataset to predict breast cancer using several machine learning methods.

## III. EXISTING SYSTEM

The majority of the most recent research publications concentrate on accurately identifying and classifying breast cancers, with a maximum accuracy of 98% attained. Furthermore, the results of the other performance indicators that were assessed, including F-score, specificity, and accuracy, were all lower than 98.2%. Furthermore, these methods have lengthy processing periods, commonly referred to as execution times. A longer time frame is viewed as a disadvantage because breast cancer detection and analysis must be completed more quickly.

#### IV. LITERATURE REVIEW

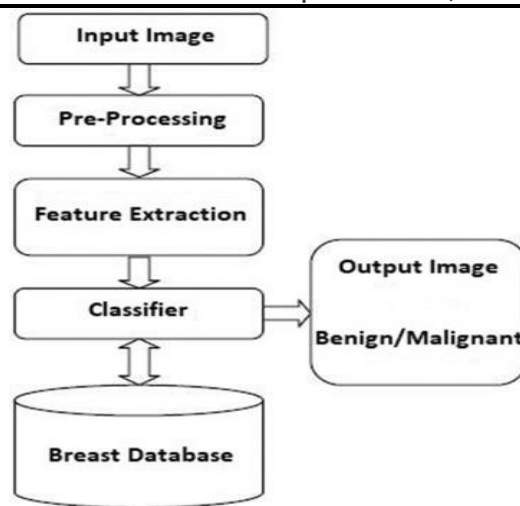
**K. A, Dr. Sharada et.al**, [1] explains it is quite difficult to diagnose and classify breast cancer. As a matter of fact, the development of a tumor or cancer is a multifaceted process that involves numerous changes to mammography images. Furthermore, several regions within the image that display varying degrees of appearance are distinguished by a range of tissues. This approach's primary benefit is image categorization for cancer prediction and performance enhancement. They used an open-source dataset to train and test their work's implementation. Python 3 was used to construct this app. The Jupyter IDE will be used for project deployment. **Bhavin Gami et.al** explains, [2] the widespread use of computer-aided detection and diagnostic (CAD) systems for the early identification of malignant cells is a result of advancements in medical technology. Deep learning's quick progress has simplified and increased the accuracy in cancer cell detection. Convolutional neural networks (CNNs) were employed by the researchers in this work to classify malignant cells. CNNs are used in image processing, segmentation, and classification. With an accuracy rate of 82%, the proposed method successfully discriminated between malignant and benign, the two types of cancer cells that are most common.

**Saad Awadh Alanazi et.al** in this paper, [3] examined the suggested system, comparing the outcomes with machine learning algorithms, that employs several convolutional neural network topologies to automatically identify breast cancer. This study suggests using a convolutional neural network method to analyze antagonistic tissue zones of ductal carcinoma in whole-slide photos to enhance the automatic diagnosis of breast cancer. A large collection of around 275,000 RGB image patches measuring 50 by 50 pixels served as the foundation for all architectures. After quantitative findings were validated using performance measures for each approach, the suggested system was determined to be successful and produced results with 87% accuracy, which may lessen the likelihood of human error throughout the diagnosis process. Furthermore, the accuracy of their system is higher than that of machine learning methods, which achieves 78% accuracy. Consequently, the accuracy of the proposed system is improved by 9% over the results of machine learning algorithms. **Y. J. Tan et.al** in this paper, [4] proposed a system that uses CNN, preprocessing is done on a collection of mammography pictures to change a human visual image into a computer visual image and set the right parameters for the CNN classifier. All modified photos are subsequently employed as training data for a CNN classifier. The findings thus indicate that the mass alone and all argument accuracy have increased from 0.75 to 0.8585 and from 0.608974 to 0.8271, respectively, indicating that the suggested technique, Convolutional Neural Net-Based Method for Detecting Breast Cancer is more accurate than other existing techniques.

**Irum Hirra et.al**, [5] explains a novel patch-based deep learning technique dubbed Pa-DBN-BC to use the Deep Belief Network (DBN) to identify and categorize breast cancer on histopathology images. An unsupervised pre-training phase and a supervised fine-tuning phase are used to extract features. From picture patches, the network automatically extracts features. To categorize the patches using histopathology images, logistic regression is applied. When the model receives the features that were taken out of the patches, it displays the outcome as a probability matrix showing either a positive sample (cancer) or a negative sample (background). The suggested model obtained an accuracy of 86% after being trained and tested on the entire slide histopathology image dataset, which included images from four distinct data cohorts. **Nur Syahmi Ismail et.al**, [6] examined the use of two deep learning model networks for breast cancer diagnosis. The entire process includes the preprocessing, classification, and performance evaluation of the images. In this work, they evaluated the ability of two deep learning model networks, VGG16 and ResNet50, to distinguish between malignant and normal tumors using the IRMA dataset. Based on the results, VGG16 outperforms ResNet50 in terms of accuracy, scoring 94% against ResNet50's 91.7%.

#### V. METHODOLOGY

This initiative uses histopathology pictures to aid in the identification of breast cancer. The project is safe, and the only person who may log in is authorized. The set of raw pictures are pre-processed to fit into the network system utilizing image resizing and image conversion. Every image is categorized according to normal, malignant, and benign—that is, healthy or infected—conditions. The project determines whether a picture is malignant or benign based on the raw histopathology image that was used as input. The relevant patient can receive a download or email of the report that is shown on the screen. This work employed the CNN model to precisely identify benign and malignant tumors from histopathology photographs.



**Fig: Data flow diagram**

### **Data Acquisition:**

Obtain a labeled dataset of histopathological images related to breast tissue, dataset includes both benign and malignant cases.

### **Preprocessing:**

Modify the histopathology images' dimensions to 140 by 92 pixels, which is the input size that the pre-trained algorithm anticipates. Pixel values should be normalized to the [0, 1] range. Consider augmenting the dataset by applying transformations (e.g., rotation, flipping) to increase diversity.

### **Transfer Learning Workflow:**

Deploy a trained deep learning model into memory. i.e. BreastCancer.h5 that has been trained on a large dataset. Freeze the layers of the pre-trained model to retain their learned features.

Add new trainable layers on top of the frozen layers. These layers will learn to transform the existing features into predictions for breast cancer. Train the new layers using your labeled histopathological dataset.

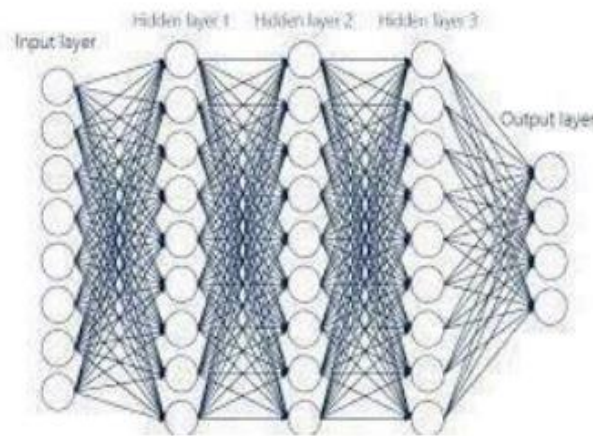
### **Interpretation and Prediction:**

Pass the pre-processed histopathological image through the model. Interpret the prediction based on the output probabilities: If the predicted probability of malignancy is greater than 0.5, classify it as "MALIGNANT." Otherwise, classify it as "BENIGN."

**Optional: Store Results:** If needed, store the prediction results (e.g., in a database) for further analysis or reporting.

### **CNN Architecture**

Given that data only moves in one direction from the inputs they receive to their outputs, CNNs are feed forward networks. Artificial neural networks (ANNs) and CNNs have a biological inspiration. Their architecture is inspired by the brain's visual cortex, which is made up of alternating layers of basic and sophisticated cells (Hubel & Wiesel, 1959, 1962). CNN designs come in a variety of forms, but they usually consist of modules that combine the convolutional and pooling (or subsampling) layers. One or more closely linked layers follow these modules layers, similar to those in a typical feed forward neural network. To create a deep model, modules are frequently layered on top of one another. CNN architecture for an imaginary application that classifies images.

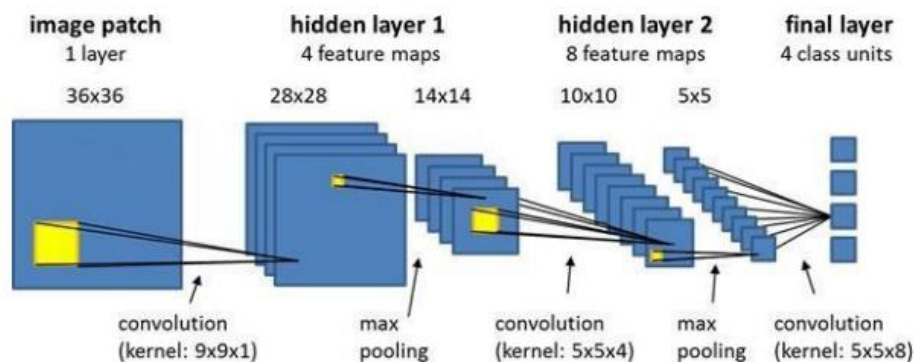


**Fig: Abstract design on CNN architecture**

### Layers of CNN:

There are three different kinds of layers in CNNs. These are pooling layers, fully connected layers and convolutional layers. The CNN architecture has been utilized when these layers are stacked. The image below shows a condensed CNN architecture for MNIST classification. Three layers: fully connected, pooling, and two input layers a basic CNN architecture made up of just five strata. There are four main components to the basic operation of the CNN example given above.

- Similar to other ANN types, the input layer will store the image's pixel data.
- The convolutional layer determines the output of neurons connected to local sections of the input by computing the scalar product between the weights of the neurons and the area related to the input volume. The fully-connected layers will then operate after that. The identical duties as standard ANNs and attempt to provide class scores from the activations in order to classify them. For better performance, ReLu has been proposed as a potential application between these layers. CNNs are able to change the original by employing this simple transformation method.



**Fig: Layers of CNN**

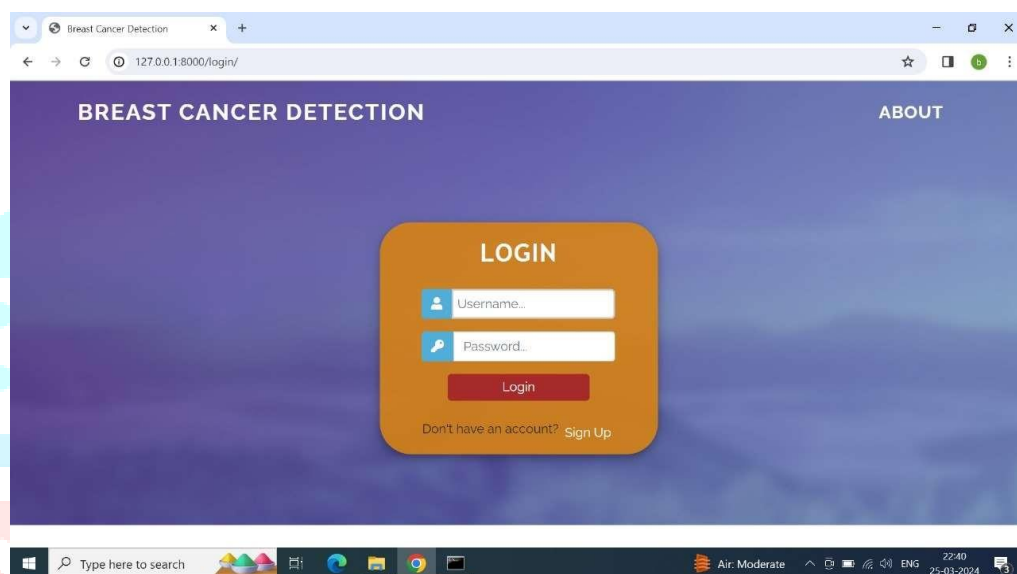
**Convolutional layers:** Convolutional layers identify the feature presentations in the input images by functioning as feature extractors. The neurons in the convolutional layers are organized into feature maps. Each neuron in a feature map has a receptive field, which is connected to a cluster of neighboring neurons in the layer above via a filter bank, which is a collection with trainable weights.

**Pooling Layer:** The goal of the pooling layers is to create spatial invariance to input translations and distortions by lowering the spatial resolution of the feature maps. In the beginning, average pooling aggregating layers were frequently used to propagate the average of all input values from a small area of an image to the following layer. Using the "MAX" function, the pooling layer scales the dimensionality of each activation mapping in the input.

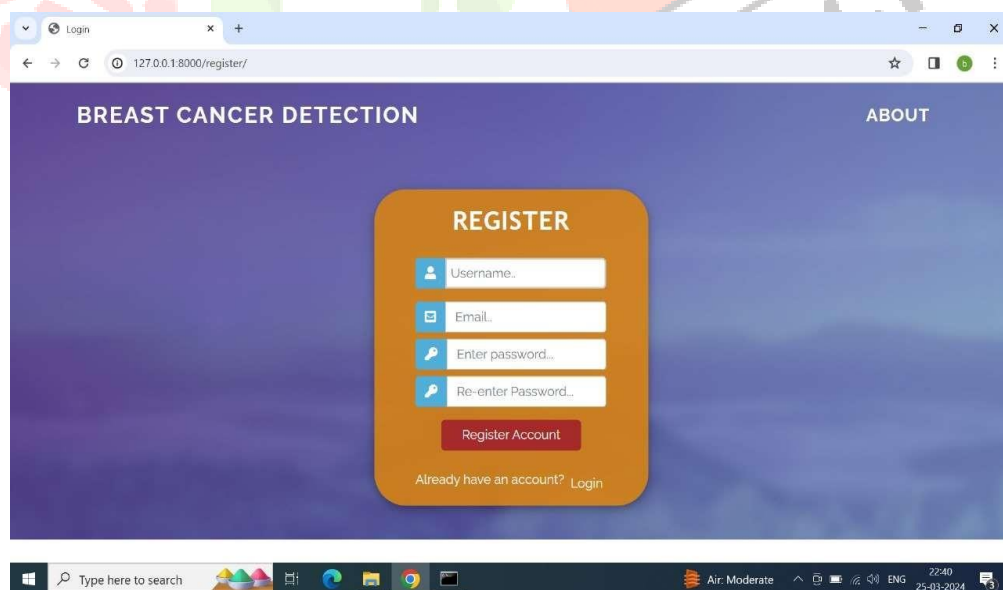
**Fully Connected Layers:** These layers, often called dense layers, work in a manner akin to traditional artificial neural networks by connecting every neuron in one layer to every other layer's neuron. Usually positioned at the conclusion of the CNN design, fully linked layers are in charge of learning complex features and forming predictions.

**CNN Algorithm:** Specifically designed convolutional neural networks (CNNs) are a kind of a neural deep learning neural network used in image and video processing. CNNs use a series of convolution and pooling layers to extract characteristics from images and videos in order to classify or recognize objects or scenes. CNNs apply several convolution and pooling layers to input pictures or videos convolution layers extract features from the input by swiping a tiny filter, or kernel, across the image or video and figuring out the dot product between the filter and the input. The output of the convolution layers is then down sampled by pooling layers to reduce the number of dimensions in the data and enhance computation performance.

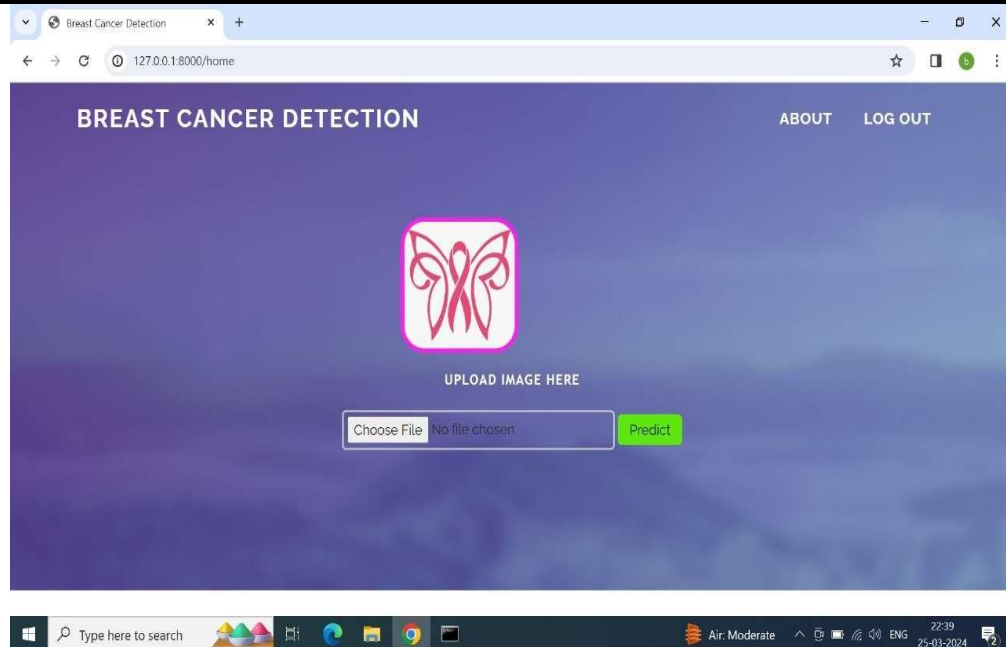
## VI. RESULTS AND DISCUSSION



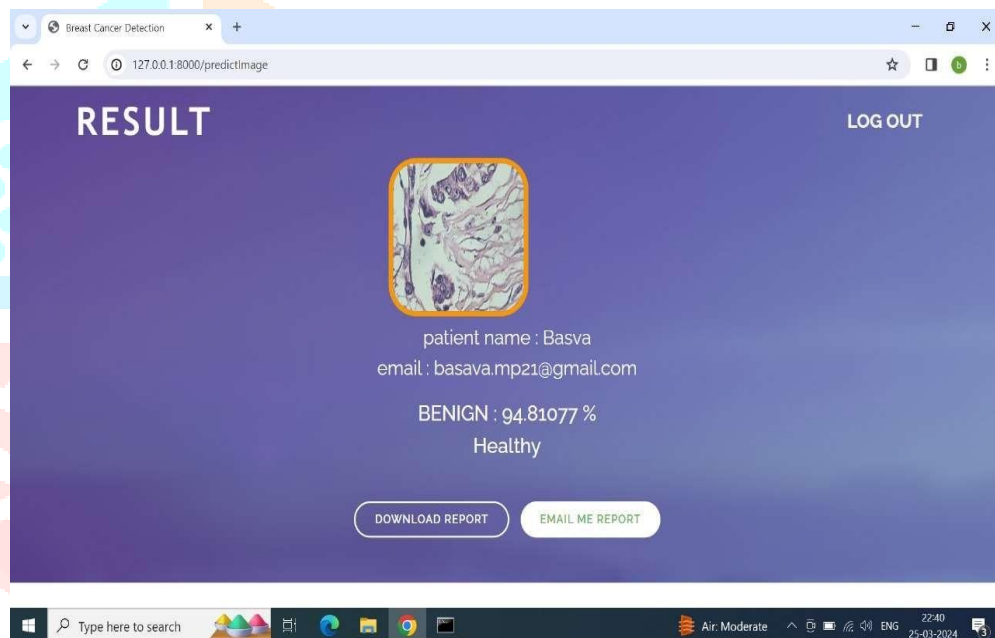
**Fig: Login Page**



**Fig: Registration Page**



**Fig: Choosing Image**



**Fig: Predicting Results**

This project is very secure the person has to login or sign up first if the person is the new user. The person has to sign in with his Username and Password. If the new user has to access the project first he/she has to register with the above credentials. To predict the disease the image has to be chosen. After predicting the result is displayed based on the accuracy whether the it is malignant or benign. The result displayed can be downloaded or can be sent a mail to the respective email id.

## VII. CONCLUSION

The completion of the Breast Cancer Histopathological Image Web Application represents a significant step towards improving the management and accessibility of breast cancer histopathological images. Future work may include enhancements such as implementing advanced search algorithms, integrating machine learning for image analysis, and expanding the application to support additional types of medical images.

## REFERENCES

- [1] K. A, Dr. Sharada et al. "Breast Cancer Detection System Using Deep Learning." International Journal for Research in Applied Science and Engineering Technology (2022): n. pag.
- [2] B Gami, Bhavin & Chauhan, Khushi & Panchal, Brijeshkumar. (2023). Breast Cancer Detection Using Deep Learning. 10.1007/978-981-19-7982-8\_8.
- [3] Saad Awadh Alanazi, M. M. Kamruzzaman, Md Nazirul Islam Sarker, Madallah Alruwaili, Yousef Alhwaiti, Nasser Alshammari, and Muhammad Hameed Siddiqi, "Boosting Breast Cancer Detection Using Convolutional Neural Network"
- [4] Tan, Y. J. et al. "Breast cancer detection using convolutional neural networks for mammogram imaging system." 2017 International Conference on Robotics, Automation and Sciences (ICORAS) (2017): 1-5.
- [5] Hirra, Irum & Ahmad, Mubashir & Hussain, Ayaz & Ashraf, M. Usman & Saeed, Iftikhar & Furqan Qadri, Syed & Alghamdi, Ahmed & Alfakeeh, Ahmed. (2021). Breast Cancer Classification From Histopathological Images Using Patch-Based Deep Learning Modeling. IEEE Access. PP. 1-1. 10.1109/ACCESS.2021.3056516.
- [6] Ismail, N. and Cheab Sovuthy. "Breast Cancer Detection Based on Deep Learning Technique." 2019 International UNIMAS STEM 12th Engineering Conference (EnCon) (2019): 89-92.

