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BREAST CANCER DETECTION USING DEEP LEARNING

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ABSTRACT

Breast cancer is the most common and rapidly developing illness in the world. Breast cancer is more commonly detected in women. Breast cancer can be controlled if it is detected early. Many instances are addressed by early discovery, which reduces the fatality rate. Many studies on breast cancer have been conducted. Machine learning is the most utilised approach in research. There have been several previous studies done using machine learning. Machine learning techniques like as decision trees, KNN, SVM, nave bays, and others provide superior performance in their respective fields. However, a newly established approach is being utilised to classify breast cancer. Deep learning is a newly developed method. Deep learning is used to compensate for the shortcomings of machine learning. Convolution neural network, Recurrent neural network, Deep Neural network, and other deep learning techniques are commonly utilised in data science. When compared to machine learning, deep learning algorithms produce greater outcomes. It extracts the photos' greatest features. CNN is employed to categorise photos in our study. Our research is mostly image-based, and CNN is the most widely used approach for image classification. The current document includes reviews of all writers.

Keywords: *Convolution neural network, Recurrent neural network, Deep neural network*

I. INTRODUCTION

Breast cancer has become one of the most frequent types of cancer among women. In 2016, around 246,660 women were diagnosed with breast cancer, representing the highest rate of 29% among all cancer types. Breast cancer is the second most common cause of mortality in women, accounting for 14% of all cancer fatalities. Each year, over 40,000 breast cancer patients die in the United States. Early detection and precise diagnosis are critical for increasing survival rates. Radiologists have obstacles in accurately detecting and diagnosing breast cancer (both normal and malignant) due to the vast number of breast pictures they must analyse every day and the difficulty of understanding the images.

Cancer develops when aberrant body cells begin to split and come into touch with regular cells, causing them to become malignant. Breast cancer is the most common and dangerous illness in the world. Breast cancer is classified as invasive or non-invasive. Invasive cancer is invasive and aggressive, and it spreads to other organs. Non-invasive malignant cells remain in their natural organ. It gradually progresses to aggressive breast cancer. Breast cancer is found in glands and milk ducts, which transport milk throughout the body. Breast cancer often spreads to other organs and causes them to become malignant. It also spreads to other organs via the circulation. Breast cancer comes in a variety of forms, each with its own pace of progression. According to the WHO, 627,000 women died because of breast cancer in 2018.

Breast cancer is the most common cause of death worldwide, although it is most common in the United States of America. Breast cancer is classified into four kinds. The first form of cancer is Ductal Carcinoma in Situ, which is in the covering of the breast milk ducts and is considered early-stage breast cancer. The second most common kind of breast cancer is diagnosed in 70-80% of cases. The third form of breast cancer is inflammatory breast cancer, which develops rapidly and strongly. In this condition, cells infiltrate the skin and lymph veins of the breast. Metastatic breast cancer, which has spread to other areas of the body, is the fourth kind of breast cancer.

Deep Learning is a developing technique in the field of machine learning that has piqued the interest of many academics and scientists. A multilayer feed forward neural network is used for deep learning. Deep learning is a type of machine learning technology that allows computers to learn from experience and data, as well as to grasp real-world problems in terms of a set of ideas and principles. As a computer learns through experience, the necessity for a human computer operator to describe all of the knowledge a computer requires diminishes. CNN's layered design assists the computer in learning properties such as form, colour, edge, and sophisticated ideas by storing them in a feature map, which is then sent into the fully connected layer to identify the picture. These hierarchies would have numerous levels in the graph.

The following is how this paper is organised: Section II provides a quick overview of the Existing Methods. Section III contains the associated proposed work. Section IV discusses the outcome of our experiment. Finally, section V closes our study effort by providing some direction for future research.

II. LITERATURE SURVEY

A literature review is the ideal place to start if you want a detailed look at what's available on a subject. The information offered here is gathered from independent sources and contains previously disclosed knowledge on a certain topic as well as information from a specific time on occasion. The goal of this type of paper, which serves as a basis for subsequent research in the topic, is to prepare for a suggested study or a synthesis of sources. It usually has a logical framework and includes summation and synthesis. A synthesis, unlike a summary, requires rearranging material from a source. As a result, it may give a new perspective on old information, or it may look back at how the profession has changed through time, including important disputes.

Depending on the circumstances, a literature review can be utilised in a variety of ways. Until recently, substantial research has been conducted to estimate electric power usage using various machine learning approaches and algorithms.

Many scientists have undertaken and accepted the task of establishing an automated computer-aided breast cancer prediction and detection system. For the creation of a CAD system, several strategies are presented. Many of the findings are discovered utilising deep learning frameworks.

Deep learning is a type of machine learning that is used for speech recognition, computer vision, video analysis, recommender systems, and natural language processing.It provides additional semantic information for obtaining higher level characteristics.

Poorolajal, J., Akbari, M. E., Ziaee, F., Karami, M., & Ghoncheh, M. [2] has introduced breast cancer screening (BCS) chart that suggests as a basic and preliminary tool to improve efficiency of screening mammography and proposed an easy and effective tool for screening, classifying the data using logistic regression very effectively.

Z. Jiao, X. Gao, Y. Wang, and J. Li [3] design a deep feature based framework for breast mass classification task. It mainly contains a convolutional neural network (CNN) and a decision mechanism. Combining intensity information and deep features automatically extracted by the trained CNN from the original image, our proposed method could better simulate the diagnostic procedure operated by doctors and achieved state-of-art performance.

J. Arevalo, F. A. González, R. Ramos-Pollán, J. Oliveira, and M. A.Lopez [4] an automatic classification of breast imaging lesions is currently an unsolved problem. This describes an innovative representation learning framework for breast cancer diagnosis in mammography that integrates deep learning techniques to automatically learn discriminative features avoiding the design of specific hand-crafted image-based feature detectors.

Susmitha Uddaraju, M. R. Narasingarao,[8] has highlighted the significance of survival concerns and illness duration treatment. Patient data after first chemotherapy is collected from the hospital and this data is then analysed using neural network. Proposed architecture gives result as the patient is responding to the chemotherapy or not. Moreover, it also gives the risk factor in surgery. Early prediction of such things gives broader idea about how treatment should go. Once the Breast cancer is detected and if chemotherapy is done, then it becomes very important to check whether patient is responding to the chemotherapy or not. So, the proposed system architecture is designed in such a way that it detects if the patient is responding to the chemotherapy or not.

Mehrdad J. Gangeh, Senior Member [11] addresses the problem by introducing a novel engineered texton-based method in order to account for volumetric information in the design of textural descriptors to represent tumor scans. Methods: A noninvasive computer-aided-theragnosis (CAT) system was developed by employing multiparametric QUS spectral and backscatter coefficient maps. The proceeding was composed of two subdictionaries: one built on the "pretreatment" and another on "week N" scans, where N was 1, 4, or 8. The learned dictionary of each patient was subsequently used to compute the model (histogram of textons) for each scan of the patient. Advanced machine learning techniques including a kernel-based dissimilarity measure to estimate the distances between "pretreatment" and "mid-treatment" scans as an indication of treatment effectiveness, learning from imbalanced data, and supervised learning.

Mandeep Rana, Pooja Chandorkar, Alishiba Dsouza, Nikahat Kazi,[12] aims is to classify whether the breast cancer is benign or malignant and predict the recurrence and non-recurrence of malignant cases after a certain period. To achieve this, we have used machine learning techniques such as Support Vector Machine, Logistic Regression, KNN and Naive Bayes. These techniques are coded in MATLAB using UCI machine learning depository. We have compared the accuracies of different techniques and observed the results. We found SVM most suited for predictive analysis and KNN performed best for our overall methodology.

III. PROPOSED ARCHITECTURE AND DESIGN

EXISTING SYSTEM

Breast cancer is the most prevalent cause of cancer fatalities. It is critical to diagnose cancer in its early stages. There are a variety of Machine Learning approaches accessible for the diagnosis of breast cancer data. This research includes a Machine Learning model for automated breast cancer diagnosis, as well as comparisons of SVM, Random Forest, KNN, Logistic Regression, and Nave Bayes classifiers. The system's performance is evaluated using no accuracy and no precision.

PROPOSED SYSTEM:

Breast cancer develops in breast cells and is a prevalent type of cancer in women. Breast cancer is the second most lethal illness in women after lung cancer. In this paper, a convolution neural network (CNN) technique is developed to improve the automated detection of breast cancer in efficient way.

PROPOSED BLOCK DIAGRAM

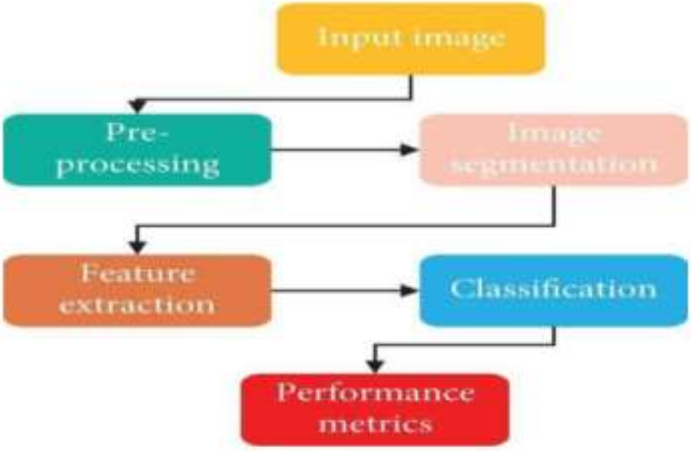

Fig 1. Proposed Block Diagram

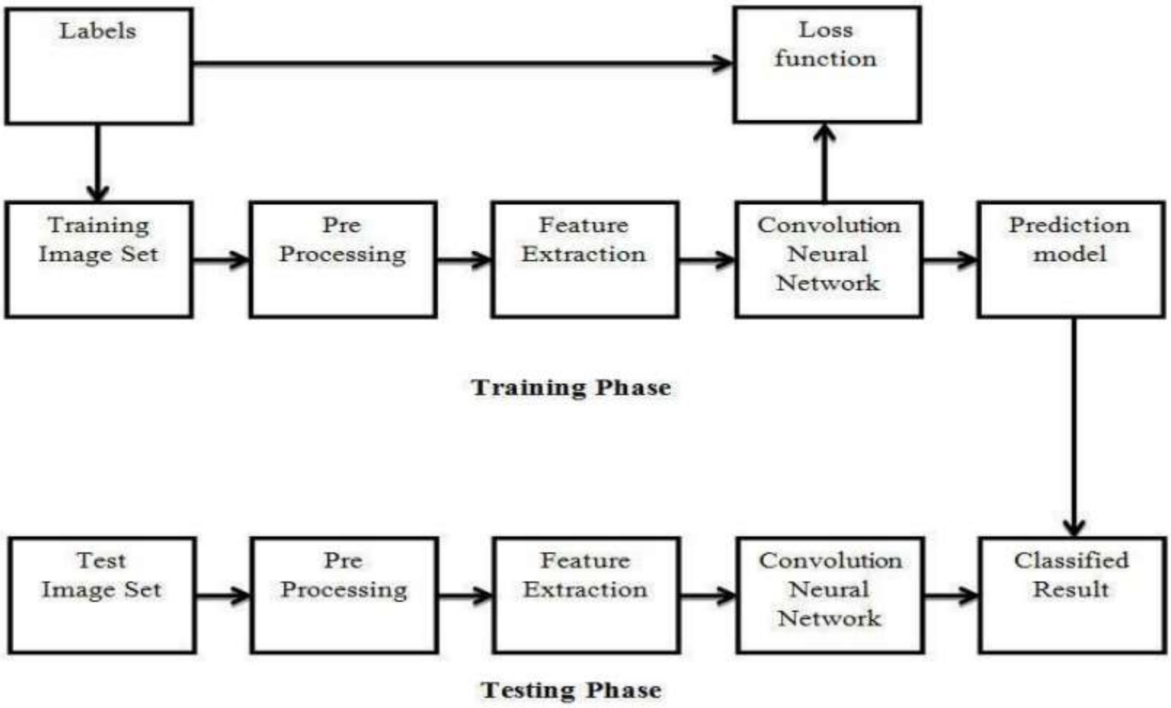

Fig 2. Proposed Flow diagram for breast cancer using CNN.

METHODOLOGY

MODULES:

- Image Data
- Pre- Processing
- Segmentation Image
- Feature Extraction
- Data Training and Testing
- Deep Learning Algorithm
- Detection

COLLECTION OF DATASETS:

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Data collecting makes extensive use of picture collections known as datasets. In computer vision, a dataset is a curated collection of digital pictures that developers use to test, train, and assess the performance of their algorithms.

Data may be obtained through many methods such as online scraping, gathering from third-party sources, or purchasing datasets from resellers, etc.

FEATURE EXTRACTION:

Feature extraction is a step in the dimensionality reduction process, whereby an initial collection of unprocessed information is separated and simplified to more manageable groupings, making processing easier. The most significant feature of these huge data sets is their enormous number of characteristics. These variables need a significant amount of computational power to process. Thus, feature extraction assists in obtaining the optimum feature from large data sets by choosing and merging variables into features, ultimately minimising the amount of data. These characteristics are simple to process while accurately and uniquely describing the real data set.

Image Processing -One of the greatest and most intriguing domains is image processing. In this area, you will essentially begin interacting with your photographs to comprehend them.

- Sort and upload your files. You've prepared your photographs, and now it's time to organise them.
- Train and be accurate.
- Using torch vision, load and normalise the CIFAR10 training and test datasets.
- Describe the Convolutional Neural Network.
- Create a loss function.
- Train the network using the practise data.
- Use the test data to put the network through its paces.

STEPS FOR CNN

Step 1: Select a Dataset...
Step 2: Get the Dataset Ready for Training...
Step 3: Gather Training Data.
Step 4: Sort the Dataset...
Step 5: Assign Labels and Features.
Normalising X and turning labels to categorical data is the sixth step.
Step 7: Separate the X and Y axes for usage in CNN.

A Convolutional Neural Network (CNN) is a form of deep learning algorithm that excels at picture detection and processing. It has several layers, including convolutional layers, pooling layers, and fully linked layers. The fundamental component of a CNN is the convolutional layers, which apply filters to the input picture to extract characteristics like as edges, textures, and forms. The convolutional layers' output is subsequently sent via pooling layers, which are used to down-sample the feature maps, lowering the spatial dimensions while maintaining the most critical information. The pooling layers' output is subsequently transmitted via one or more fully connected layers, which are used to predict or categorise.

Convolutional Neural Network Layers

A convolution neural network includes numerous hidden layers that aid in picture information extraction. CNN's four critical levels are as follows:

1. ReLU layer 2. Convolution layer 3. Pooling layer
4 fully connected.
5. softmax

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This is the initial stage in obtaining useful information from an image. Several filters conduct the convolution action in a convolution layer. Every image is seen as a pixel value matrix.

Consider the 5x5 picture below, where the pixel values are either 0 or 1. There is also a filter matrix with a 3x3 dimension. To obtain the convolved feature matrix, move the filter matrix across the picture and compute the dot product.

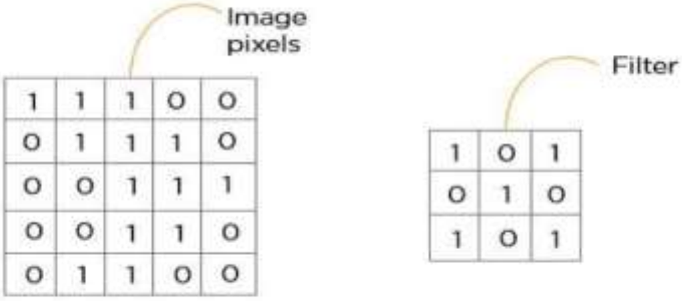

Fig 3. Convolution of image

ReLU layer

The rectified linear unit is abbreviated as ReLU. After the feature maps have been removed, they must be moved to a ReLU layer.

ReLU conducts an element-by-element procedure, setting all negative pixels to 0. It adds nonlinearity to the network, and the result is a corrected feature map. The graph of a ReLU function is shown below:

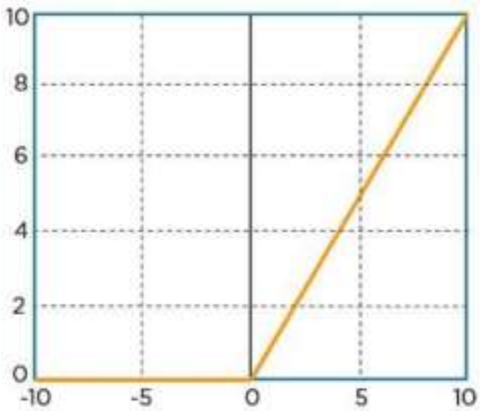

Fig 4. ReLU Graph

$$R(z) = \max(0, z)$$

Pooling Layer

Pooling is a type of down sampling that decreases the dimensionality of a feature map. The corrected feature map is now processed by a pooling layer to produce a pooled feature map.

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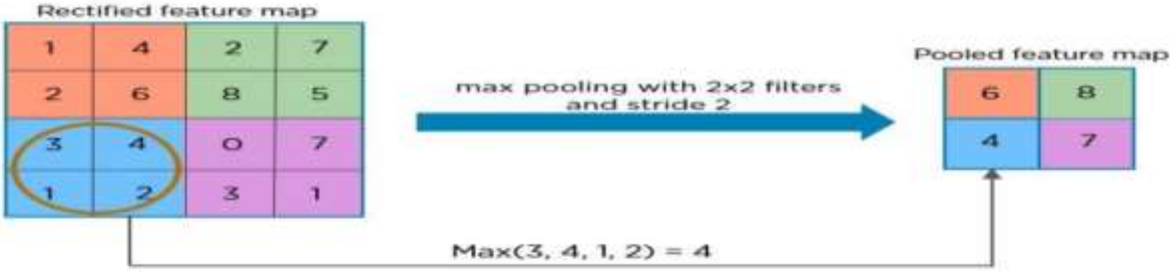

Fig 5. Pooling Layer

The pooling layer employs multiple filters to recognise various aspects of the picture, such as edges, corners, shape etc.

So far, here is how the structure of the convolution neural network looks:

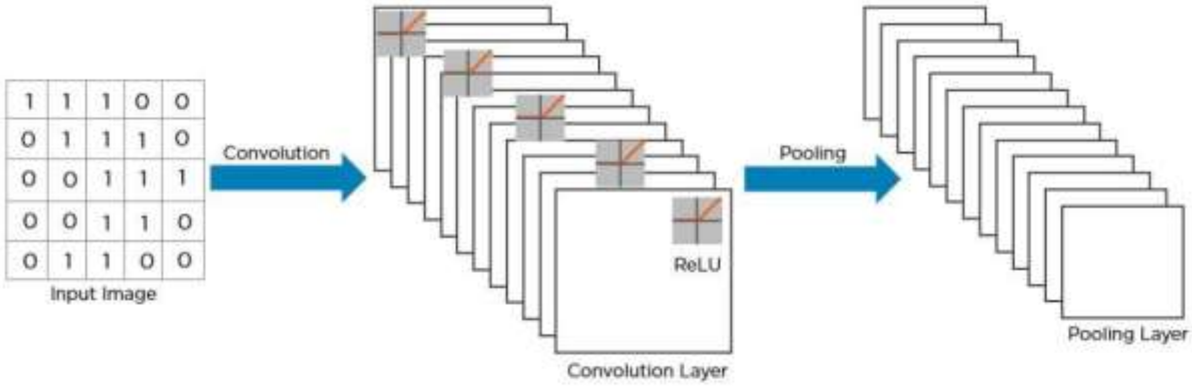

Fig 6. Flattening

Flattening is used to combine all the 2-Dimensional arrays produced by pooling feature maps into a single long continuous linear vector.

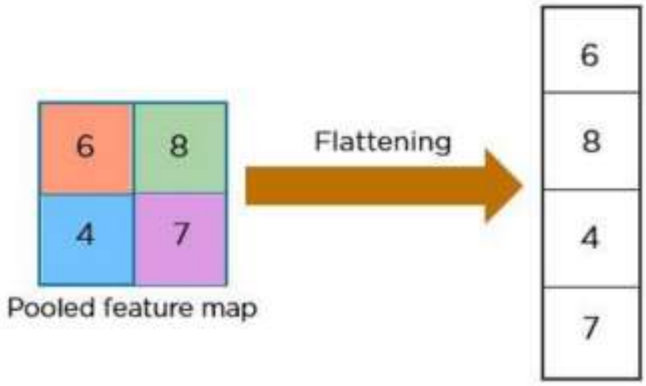

Fig 7. Flattening

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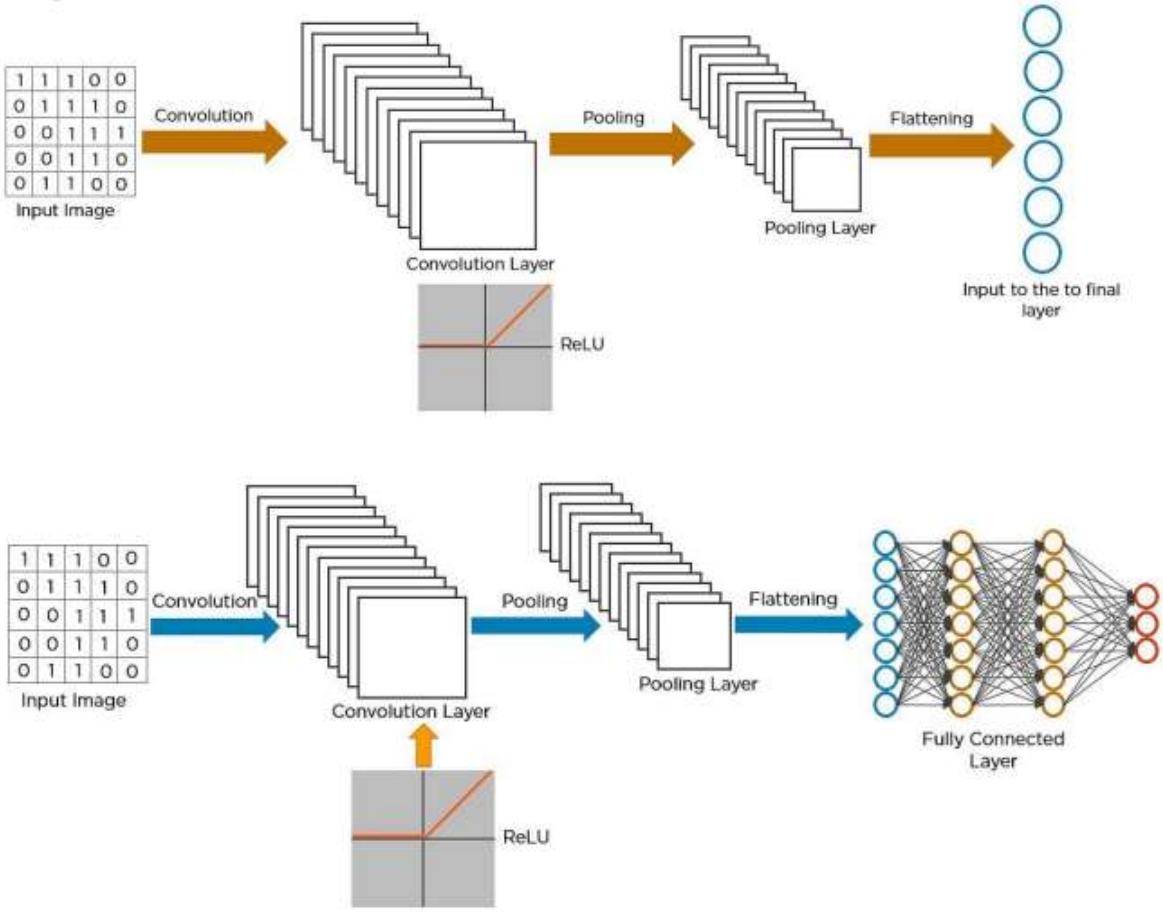

Fig 8. Overall Architecture of The Proposed CNN model for breast cancer classification

As a result, a Convolutional kernel learns to recognise the feature of a picture or image that is visible in the feature map. To reduce computational complexity and provide a diverse levelling collection of image features, each grouping of convolution layers is followed by a pooling layer, a work procedure evocative of simple and complicated cells in the primary visual cortex [3][6]. The maximum pooling layer is used to minimise picture size by picking the most essential feature and building a feature map for each image. Max pooling discards low level feature values while maintaining high level feature values in the feature vector. As a result, max pooling can improve translation invariance. CNNs are often made up of a few sets of Convolutional, Rectified Linear Unit (ReLU), pooling layers and fully connected layers.

A pooling layer can be placed between two Convolutional layers. The major reason for including pooling layers between Convolutional layers is to lower the spatial size of a picture. As a result, it helps to minimise the number of parameters and computations required by the neural network, which helps to reduce overfitting.

The pooling (sub sampling) layer spatially down samples the picture volume and is independent in each depth slice of the input volume. The pool operator is used to resize an image's input along its width and height. In pooling, the max function returns the largest value of the pixel in a window.

In a completely connected layer, neurons are fully linked to all the previous layer's activation nodes, and their activation value may be determined via matrix multiplication followed by the addition of a bias offset. The net output is in the last completely linked layer, and the final classification process is completed in these layers.

CONVOLUTIONAL NEURAL NETWORK TRAINING

Convolutional Neural Networks function with high-resolution pictures, and they are mostly employed for breast cancer Histopathological image categorization. Using a deep neural network [10] with a bigger quantity of picture data will result in overfitting, and many parameters will need to be adjusted in the hidden layers of neurons, increasing the model's complexity. As a result, the time required to train the model and update the parameter might be rather lengthy. CNN is primarily utilised for the extraction of filters or tiny patches of image that are then used to train the network, and the combination of these filters generates a feature map that aids in image recognition. Only tiny patches of pictures are utilised for training to learn the characteristics and parameters of CNN. The fundamental concept is to extract the characteristics of a high-resolution image.

The proposed Convolutional Neural Network approach collects characteristics from the BreakHis dataset picture and classifies it as benign or malignant tumour.

In our model, the CNN network was employed for both feature extraction and classification. The last layer (Softmax layer) is used to categorise the picture into following groups.

ADVANTAGES:

- Little reliance on pre-processing
- Reducing the requirement for human labour in establishing its functions.
- It is simple to grasp and quick to apply.
- It has the greatest accuracy of any algorithm for predicting breast cancer photos.
-

IV. RESULT AND DISCUSSION

The DDSM comprises digitised film mammography in the now-outdated lossless-JPEG format. We utilised a subsequent version of the database called CBIS-DDSM, which contains pictures in conventional DICOM format. The dataset, which comprised 2478 mammography pictures from 1249 women, was obtained from the CBIS-DDSM website and contained craniocaudal (CC) as well as mediolateral oblique (MLO) views for most of the tests. In this investigation, each perspective was regarded as a single picture. At the patient level, we randomly divided the CBIS-DDSM dataset 85:15 to establish distinct training and test sets. To produce an independent validation set, the training data was divided 90:10 again. The splits were done in a stratified manner to ensure that the training, validation, and test sets all had the same proportion of cancer cases. The training, validation, and testing sets each had 1903, 199, and 376 photos, respectively.

This paper demonstrates that correct categorization of screening mammograms may be obtained using a deep learning model trained end-to-end, with only clinical ROI annotations used in the initial stage. Once the whole image classifier has been generated, it may be fine-tuned using new datasets that lack ROI annotations, even if the pixel intensity distributions change, as is frequently the case with datasets produced from different mammography platforms.

These findings suggest that deep learning algorithms can outperform traditional commercial CAD systems, such as iCAD SecondLook 1.4 and R2 ImageChecker Cenova 1.0, which do not use deep learning and have an average AUC of 0.72. When compared to previous deep learning methods that achieved AUCs in the range of 0.65-0.97 on the DDSM and INbreast databases, as well as in-house datasets, our all-convolutional networks have highly competitive performance and are more generalizable across different mammography platforms.

According to two recent investigations, a new commercial CAD system, Transpara 1.4.0, achieved an AUC of 0.89 when used to help radiologists16 and 0.84 when used alone.

This commercial CAD uses CNNs trained on lesion annotations from 9000 cancer-related mammograms to provide patch-level ratings; the scores for all identified areas were then pooled to give an examination-level score. Without lesion annotations, commercial CAD cannot be easily fine-tuned on different mammography datasets, to our knowledge.

V. CONCLUSION AND FUTURE IMPROVEMENTS

As we all know, the deep learning approach convolutional neural network is commonly used for picture dataset categorization, which is why we utilised it in our project. This study used data from the Break His dataset to classify breast cancer. In this effort, we proposed using transfer learning to classify breast cancer histology pictures. To detect breast cancer, we employed the Inception v3 model using the Break His dataset.

In the future, we will experiment with new characteristics as well as with real-world picture datasets to attain the greatest results and accuracy for cancer detection. In addition to breast cancer, we will test this approach on other types of cancer. In this research, we simply employed a CNN with parameter variation to categorise the image. Even if the efficiency is rather high, there is still potential for improvement. Our next goal is to get as close to 100% accuracy as possible.

REFERENCES

1. R. L. Siegel, K. D. Miller, and A. Jemal, “Cancer statistics, 2016,” CA Cancer J Clin, vol. 66, pp.7-30, 2016.

2. Poorolajal, J., et al., Breast cancer screening (BCS) chart: a basic and preliminary model for making screening mammography more productive and efficient. J Public Health (Oxf), 2017: p. 1-8.

3. Z. Jiao, X. Gao, Y. Wang, and J. Li, “A deep feature-based framework for breast masses classification,” Journal of Neurocomputing, vol. 197, pp. 221-231, 2016.

4. J. Arevalo, F. A. González, R. Ramos-Pollán, J. Oliveira, and M. A.Lopez, “Representation learning fo mammography mass lesion classification with convolutional neural networks,” Comput. Methods Program Biomed, vol. 127, pp. 248- 257, 2016.

5. Deng, L., Yu, D.: Deep Learning: Methods and Applications. Now publishers, Boston (2014).

6. Krizhevsky, A., I. Sutskever, and G.E. Hinton. Imagenet classification with deep convolutional neural networks. in Advances in neural information processing systems. 2012.

7. Ch. Shravya, K. Pravalika, Shaik Subhani, “Prediction of Breast Cancer Using Supervised Machine Learning Techniques International”, Journal of Innovative Technology and Exploring Engineering (IJITEE) Volume-8 Issue-6, April 2019.

8.Susmitha Uddaraju, M. R. Narasingarao, “A Survey of Machine Learning Techniques Applied for Breast Cancer Prediction”, International Journal of Pure and Applied Mathematics (IJPAM) Volume 117 No. 19 2017.

9.Priyanka Gupta, Prof. Shalini L, “Analysis of Machine Learning Techniques for Breast Cancer Prediction”, International Journal of Engineering and Computer Science (IJECS) Volume 7 Issue 5 May 2018.

10.Ravi Aavula, R. Bhramaramba, “An Extensible Breast Cancer Prognosis Framework for Predicting Susceptibility, Recurrence and Survivability”, International Journal of Engineering and Advanced Technology (IJEAT) Volume-8 Issue-5, June 2019.

11.Mehrdad J. Gangeh, Senior Member, IEEE, Simon Liu, Hadi Tadayyon, and Gregory J. Czarnota, "Computer Aided Theragnosis Based on Tumour Volumetric Information in Breast Cancer", DOI 10.1109/TUFFC.2018.2839714, IEEE

12.Mandeep Rana, Pooja Chandorkar, Alishiba Dsouza, Nikahat Kazi, "Breast Cancer Diagnosis and Recurrence. Prediction using Machine Learning techniques", IJRET: International Journal of Research in Engineering and Technology Volume: 04 Issue: 04 Apr-2015.