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Breast Cancer Detection Using Machine Learnings

Mr. Girish Singh Bisht, Deepak Sharma , Ayush Tyagi, Dhruv Chaudhary
Department of Computer Science and Engineering
Tula's Institute of Technology, Dehradun, India
girish@tulas.edu.in, deepak.202204128@tulas.edu.in,
ayush.202204191@tulas.edu.in, dhruv.202204049tulas.edu.in

Abstract: *Breast cancer remains one of the most serious health concerns and is responsible for a large number of cancer-related deaths across the world. Early identification of the disease plays a vital role in increasing treatment effectiveness and improving survival rates. With the advancement of Artificial Intelligence and Machine Learning, automated diagnostic systems have become valuable tools for assisting medical professionals in cancer detection.*

This study proposes a breast cancer detection framework based on Machine Learning techniques. The proposed model utilizes a Convolutional Neural Network (CNN) to classify breast cancer images and employs Recursive Feature Elimination (RFE) to identify the most relevant features from the dataset. To evaluate the effectiveness of the approach, the performance of CNN is compared with several widely used classification algorithms, including Support Vector Machine (SVM), Random Forest, K-Nearest Neighbour (KNN), Logistic Regression, and Naïve Bayes.

The experiments are conducted using the BreaKHis 400X breast cancer dataset. Model performance is assessed using evaluation parameters such as accuracy and precision. The CNN architecture incorporates the Rectified Linear Unit (ReLU) activation function to enhance feature learning and improve classification performance. The obtained results indicate that Machine Learning-based approaches can provide reliable support for the early detection and classification of breast cancer, thereby contributing to more effective healthcare decision-making.

Keywords: Breast Cancer Detection, Machine Learning, Deep Learning, Convolutional Neural Network, Recursive Feature Elimination, Medical Image Classification, BreaKHis Dataset, Artificial Intelligence

INTRODUCTION

Breast cancer is one of the most common and life-threatening diseases affecting women worldwide. The chances of successful treatment increase significantly when the disease is identified during its early stages. As a result, the development of accurate and efficient diagnostic systems has become an important area of research in the healthcare domain.

Recent advancements in Machine Learning and Artificial Intelligence have enabled the creation of automated systems capable of assisting medical professionals in detecting breast cancer. These intelligent systems analyze medical data and identify patterns that may indicate the presence of malignant or benign tumors. Automated diagnosis not only improves detection accuracy but also reduces the time required for clinical evaluation.

This study presents a Machine Learning-based framework for breast cancer detection using a Convolutional Neural Network (CNN) as the primary classification model. Recursive Feature Elimination (RFE) is employed to select the most relevant features and improve model performance. Furthermore, the effectiveness of the proposed approach is compared with several widely used classification techniques, including Support Vector Machine (SVM), Random Forest, K-Nearest Neighbour (KNN), Logistic Regression, and Naïve Bayes.

The experimental analysis is performed using the BreaKHis 400X dataset. The performance of the developed system is evaluated using metrics such as accuracy and precision. The CNN architecture incorporates the Rectified Linear Unit (ReLU) activation function to enhance learning capability and generate reliable prediction probabilities. The results

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demonstrate the potential of Machine Learning techniques in supporting early breast cancer diagnosis and improving healthcare decision-making.

II. LITERATURE REVIEW

This section presents an overview of previous studies conducted by researchers in the field of breast cancer diagnosis using various Machine Learning and Deep Learning techniques.

Arpita Joshi and Dr. Ashish Mehta [1] performed a comparative analysis of several classification algorithms, including K-Nearest Neighbour (KNN), Support Vector Machine (SVM), Random Forest, and Decision Tree techniques such as Recursive Partitioning and Conditional Inference Tree. Their experiments were conducted using the Wisconsin Breast Cancer Dataset obtained from the UCI Machine Learning Repository. The results demonstrated that KNN achieved the highest classification performance, followed by SVM, Random Forest, and Decision Tree methods.

David A. Omondiagbe, Shanmugam Veeramani, and Amandeep S. Sidhu [2] evaluated the effectiveness of Support Vector Machine, Artificial Neural Network, and Naïve Bayes algorithms on the Wisconsin Diagnostic Breast Cancer (WDBC) dataset. Their study incorporated feature selection and feature extraction approaches to enhance model performance. Based on the experimental findings, the SVM-LDA model was identified as the most suitable approach among the evaluated techniques.

Kalyani Wadkar, Prashant Pathak, and Nikhil Wagh [3] carried out a comparative study between Artificial Neural Networks (ANN) and Support Vector Machines (SVM). In addition, they integrated advanced classifiers such as Convolutional Neural Networks (CNN), K-Nearest Neighbour (KNN), and Inception V3 to improve dataset processing and classification accuracy. Their analysis revealed that ANN delivered better overall performance and efficiency compared to SVM.

Anji Reddy Vaka, Badal Soni, and Sudheer Reddy K. [4] proposed a breast cancer detection framework utilizing multiple Machine Learning and Deep Learning techniques, including Naïve Bayes, Support Vector Machine, Bi-clustering AdaBoost, RCNN, and Hybrid Attention-Based Bidirectional Recurrent Neural Networks (HA-BiRNN). The proposed methodology was compared with conventional approaches to evaluate its effectiveness. Experimental results indicated that the Deep Neural Network-based approach provided superior performance, improved efficiency, and better image quality, making it more suitable for modern medical diagnostic systems.

The reviewed studies demonstrate that Machine Learning and Deep Learning algorithms play a significant role in the accurate detection and classification of breast cancer. The findings suggest that advanced neural network models often outperform traditional classification techniques, highlighting the growing importance of intelligent healthcare systems in supporting early diagnosis and treatment planning.

Monica Tiwari, Rashi Bharuka, Praditi Shah, and Reena Lokare [5] presented a breast cancer prediction framework that combines both Machine Learning and Deep Learning approaches. Their study evaluated algorithms such as Logistic Regression, Random Forest, K-Nearest Neighbour, Decision Tree, Support Vector Machine, and Naïve Bayes, along with Deep Learning models including Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN). The experimental findings indicated that Deep Learning models achieved superior performance, with CNN attaining an accuracy of 97.3% and ANN reaching 99.3%, outperforming the traditional Machine Learning techniques.

Abdullah-Al Nahid and Yinan Kong [6] proposed an image-based breast cancer detection approach utilizing several classification methods, including Convolutional Neural Networks (CNN), conventional Neural Networks (NN), Random Forest (RF), Support Vector Machines (SVM), and Bayesian classifiers. Their research demonstrated that CNN produced the most effective results due to its capability of automatically extracting global image features through convolutional kernels, thereby enhancing classification performance.

K. Anastraj, Dr. T. Chakravarthy, and K. Sriram [7] conducted a comparative analysis of various classification techniques, namely Backpropagation Networks, Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Support Vector Machines (SVM), using the Wisconsin Breast Cancer dataset. Deep learning architectures

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combined with ALEXNET-based feature extraction were employed to classify benign and malignant tumors. The experimental outcomes revealed that SVM achieved the highest classification accuracy of approximately 94%.

S. Vasundhara, B. V. Kiranmayee, and Chalumuru Suresh [8] proposed an automated system for classifying mammogram images into Normal, Benign, and Malignant categories. Their work compared the performance of Support Vector Machines, Random Forest, and Convolutional Neural Networks. The results indicated that CNN delivered the most reliable performance by effectively utilizing filtering and morphological operations for mammogram image analysis.

Muhammet Fatih Ak [9] utilized a breast cancer dataset collected by Dr. William H. Walberg from the University of Wisconsin Hospital. The study incorporated data visualization and several Machine Learning algorithms, including Logistic Regression, K-Nearest Neighbour, Support Vector Machine, Naïve Bayes, Decision Tree, Random Forest, and Rotation Forest. Experiments were performed using R, Minitab, and Python environments. The findings showed that Logistic Regression, when applied with all available features, achieved the highest classification accuracy of 98.1%.

Sivapriya J., Aravind Kumar V., Sidharth Sai S., and Sriram S. [10] evaluated the performance of Support Vector Machine, Logistic Regression, Naïve Bayes, and Random Forest algorithms using the Wisconsin Breast Cancer dataset. The experiments were implemented on the ANACONDA Data Science Platform. Their results demonstrated that the Random Forest classifier achieved the best performance, obtaining an accuracy of 99.76% while maintaining the lowest error rate among all evaluated methods.

Hiba Asria, Hajar Mousannif, Hassan Al Moatassime, and Thomas Noel [11] carried out a comparative study involving Support Vector Machine (SVM), Decision Tree (C4.5), Naïve Bayes (NB), and K-Nearest Neighbour (K-NN) classifiers on the Wisconsin Breast Cancer dataset. The study was implemented using the WEKA data mining tool. Experimental results revealed that SVM provided the highest accuracy of 97.13% and produced the lowest classification error compared to the other algorithms.

Dana Bazazeh and Raed Shubair [12] compared three widely used Machine Learning techniques: Support Vector Machine (SVM), Random Forest (RF), and Bayesian Networks (BN). The Wisconsin Breast Cancer dataset was used for training and evaluation. Their analysis showed that classification performance varied depending on the selected model. SVM achieved superior results in terms of accuracy, precision, and specificity, whereas Random Forest demonstrated a greater capability for correctly identifying tumor classes.

III. METHODOLOGY

DATA SET

The data utilized in the experiments was sourced from Kaggle, specifically from the BreakHistDataset. This dataset comprises four directories, each representing a different image magnification: 100X, 200X, 400X, and 40X. In total, the dataset contains 7,858 instances, distributed across these magnification directories. Within each magnification directory, there are two sub-directories, categorizing the tumors as either Benign or Malignant.

PREPROCESSING

1) Feature Selection

Feature selection is crucial for machine learning models as it eliminates ambiguity, simplifies data complexity, and reduces dataset size, thereby facilitating easier model training and decreasing training time. It also helps prevent overfitting. Choosing the optimal feature subset enhances model accuracy. Common feature selection techniques include wrapper methods, filter methods, and embedded methods.

2) Recursive Feature Elimination

Recursive Feature Elimination (RFE) is a wrapper-type feature selection algorithm. It employs another machine learning algorithm internally to assist in feature selection, distinguishing it from filter-based methods that score and select features based on their scores. RFE technically functions as a wrapper-style algorithm that also incorporates

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filter-based selection. It operates by iteratively removing features, starting with all features in the training dataset, until the desired number of features remains. This process involves fitting the core machine learning algorithm, ranking features by importance, discarding the least important ones, and re-fitting the model until the target number of features is achieved.

3) Segmentation

Segmentation refers to the process of dividing images into smaller patches, ranging from 2x2 to 10x10. This operation trains the system to identify critical regions of interest for detecting breast cancer (BC) by removing irrelevant data, thus enabling earlier tumor identification. The K-means clustering algorithm, which groups similar objects together, is often relied upon for segmentation to achieve better results, particularly when similar objects are present within a group. This method is also faster compared to processing scattered data [1].

CLASSIFIERS

4) Support Vector Machine (SVM)

The goal of the Support Vector Machine (SVM) algorithm is to identify a hyperplane in an N-dimensional space (where N is the number of features) that effectively separates data points into distinct classes. While multiple hyperplanes can separate two classes, SVM aims to find the one with the maximum margin, meaning the greatest distance between data points of each class. Hyperplanes serve as decision boundaries for classification, with data points on either side belonging to different classes. The dimensionality of the hyperplane is determined by the number of features. Support vectors are data points situated closest to the hyperplane, influencing its position and orientation. By utilizing these support vectors, the classifier's margin is maximized. Removing support vectors would alter the hyperplane's position. SVM is recognized as a highly effective classifier, particularly for data with a clear separation margin and high dimensionality. However, it is not ideal for very large datasets due to its lengthy training time and can underperform with noisy data.

5) K-Nearest Neighbor (KNN)

K-Nearest Neighbor (KNN) is a straightforward supervised learning algorithm. It operates on the principle of similarity, categorizing a new data point based on its resemblance to existing data points. The KNN algorithm stores all available data and classifies a new point by identifying its closest neighbors. The process involves finding data points within a certain proximity to the new point and then sorting these closest points by distance from the new point. Euclidean distance is a commonly used metric for this measurement. Subsequently, a predefined number of the closest points are selected and used to assign the new data point to a category. The number of points (K) chosen is typically an odd number to avoid ties in classification. KNN is simple to implement and can handle large datasets; however, its computational cost is high due to the need to calculate distances between the new point and all training samples. Additionally, determining the optimal value for K can increase the algorithm's complexity.

6) Random Forest

Random Forest is a supervised learning algorithm that constructs an ensemble of decision trees. A decision tree is a hierarchical structure where nodes represent conditions on features, and branches lead to leaf nodes that determine class labels. Decision trees can be built using Recursive Partitioning or Conditional Inference Tree methods. Recursive Partitioning involves a step-by-step process of splitting nodes based on attribute value tests until subsets at a node share the same target variable value. Conditional Inference Trees employ a statistical approach using non-parametric tests corrected for multiple testing to prevent overfitting. Random Forest is well-suited for modeling high-dimensional data, capable of handling missing, continuous, categorical, and binary data. However, for very large datasets, the size of the trees can consume significant memory. It can also be prone to overfitting, necessitating hyperparameter tuning [1].

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7) Logistic Regression

While linear regression uses a hyperplane to predict a continuous dependent variable from independent variables, logistic regression is employed for categorical data. Logistic Regression predicts a binary outcome (true or false) rather than a continuous value, making it suitable for classification tasks. The sigmoid function is used to transform independent variables into probabilities ranging from 0 to 1 concerning the dependent variable. This ability to provide probabilities and classify new samples using both continuous and discrete measurements makes it a popular machine learning algorithm. A limitation of Logistic Regression is its assumption of a linear relationship between the dependent and independent variables.

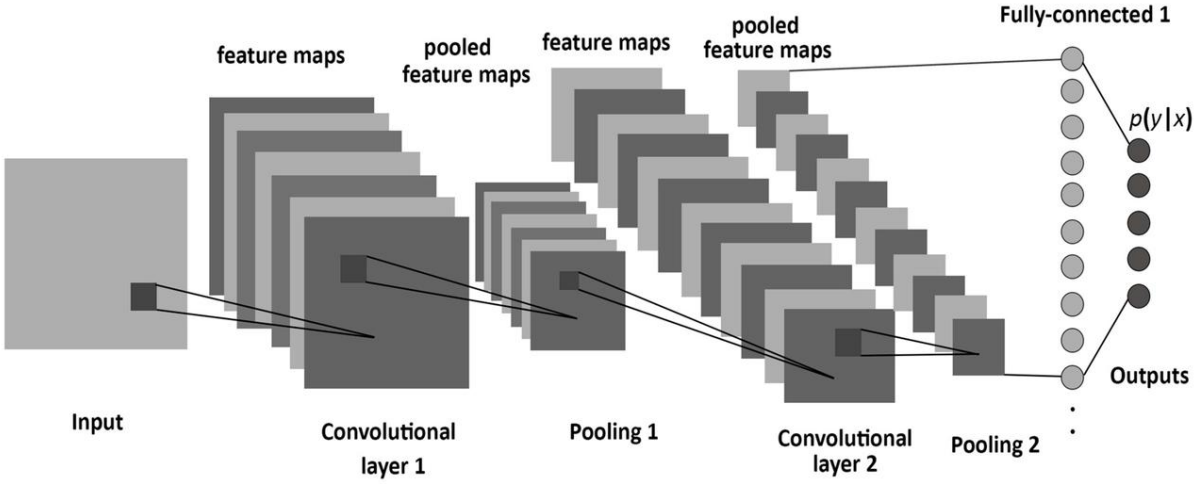
8) Naïve Bayes

The Naïve Bayes classifier is a supervised learning algorithm used for classification, based on Bayes' theorem. It calculates the probability of an event occurring given that another event has already happened. It is recognized as one of the simplest yet most powerful machine learning algorithms, with wide applications across various industries. Naïve Bayes operates under the assumption that all predictors are independent of each other.

IV. PROPOSED METHODOLOGY

The proposed methodology will help us to distinguish between malignant and benign tumor at a faster rate. CNN being a complex and complicated classifier can extract vital features automatically without depending on preprocessing. It is more proficient because it filters the important parameters and also is flexible being capable to work exceptionally well on image data.

A schematic structure of CNN is given below:



The primary objective of this project is to classify breast tumors as either benign or malignant using a Convolutional Neural Network (CNN) model implemented with the Keras framework. The developed system aims to assist in the early detection of breast cancer by analyzing medical image data and generating accurate predictions. The effectiveness of the proposed CNN model is further evaluated by comparing its performance with other machine learning classifiers.

The model development and evaluation process consists of the following steps:

Importing the required Python libraries and dependencies.

Creating image and label dictionaries from the dataset.

Assigning class labels based on image categories.

Normalizing the image dataset to improve model performance.

Dividing the dataset into training and testing subsets.

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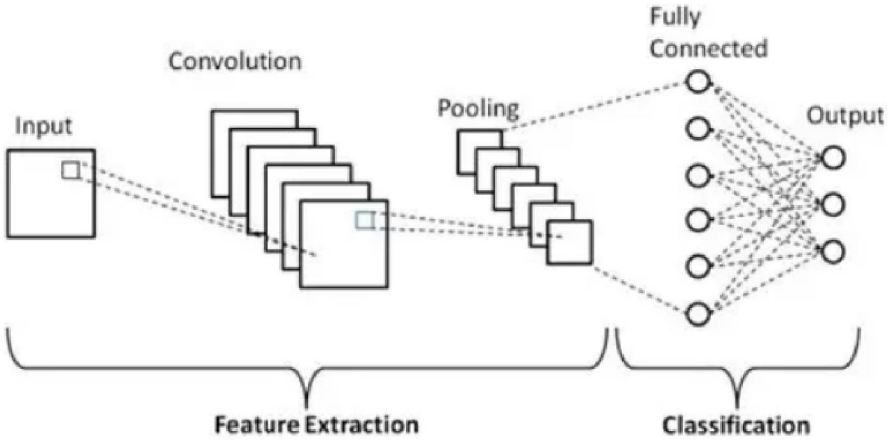
Designing and implementing the Convolutional Neural Network (CNN) architecture.
Performing cross-validation and comparing the CNN model with other classification algorithms.
Evaluating and testing the final model using performance metrics.Building of CNN:

Layers in Convolutional Neural Network:



Layer 1: Convolutional Layer

The convolutional layer is the fundamental building block of a Convolutional Neural Network (CNN) and is responsible for extracting meaningful features from input images. In this process, an image is represented as a matrix of pixel values, while small matrices known as filters or kernels are applied to identify important patterns and visual characteristics.

During convolution, a filter moves across the image and performs mathematical operations on the corresponding pixel values. The result of these operations is a feature map that highlights significant information present in the image. For example, a 3×3 filter can be applied to a 5×5 image by sliding it across the image and computing the dot product at each position. This process enables the network to detect various visual features such as edges, textures, and shapes.

The first convolutional layer processes the raw image and extracts basic visual patterns, commonly referred to as low-level features. These features may include simple edges, corners, and contours. The extracted feature maps are then passed through an activation function such as Rectified Linear Unit (ReLU), which introduces non-linearity into the network and improves learning capability.

Subsequent convolutional layers receive the feature maps generated by previous layers rather than the original image. This allows the network to combine simple patterns into more complex structures. As the data progresses through deeper layers of the CNN, the extracted features become increasingly sophisticated. Intermediate layers identify mid-level features, while deeper layers capture high-level features that are useful for distinguishing between different classes, such as benign and malignant tumors.

This hierarchical feature extraction capability makes CNNs highly effective for image classification and medical image analysis applications.

(ReLU) is one of the most widely used activation functions in Convolutional Neural Networks (CNNs). After the convolution operation generates feature maps, these feature maps are passed through the ReLU layer to introduce non-linearity into the network.

The ReLU function operates on each element of the feature map individually. It converts all negative values to zero while retaining positive values unchanged. Mathematically, the ReLU function can be represented as:

[
ReLU(x) = \max(0, x)
]

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By eliminating negative values, ReLU helps the network focus on important features and reduces computational complexity. The introduction of non-linearity enables the CNN to learn complex patterns and relationships within image data that cannot be captured using linear operations alone.

In a CNN architecture, convolution and ReLU layers work together repeatedly. The convolutional layers extract relevant features from the input image, while the ReLU layers enhance the learning capability of the network by transforming the extracted features into rectified feature maps. Through multiple convolution and ReLU operations, the network progressively identifies significant image characteristics, which are later used for accurate classification and prediction tasks.

The simplicity, efficiency, and ability to accelerate model training have made ReLU one of the most preferred activation functions in modern deep learning applications.

Layer 2: Pooling Layer

The Pooling Layer is an essential component of a Convolutional Neural Network (CNN) that helps reduce the spatial dimensions of feature maps generated by convolutional layers. By decreasing the size of these feature maps, pooling reduces the number of parameters and computational operations required during training and prediction, thereby improving the overall efficiency of the network.

The primary function of the pooling layer is to summarize important information from a specific region of the feature map. Instead of preserving every feature value, pooling extracts the most significant characteristics and produces a condensed representation of the input data. This process helps retain relevant information while removing redundant details.

One of the most commonly used pooling techniques is **Max Pooling**, where the maximum value within a selected region is chosen as the representative value. Another technique is **Average Pooling**, which calculates the average value of the selected region.

By reducing the feature map dimensions, pooling makes the model less sensitive to small variations in the position, orientation, and scale of features within an image. As a result, the CNN becomes more robust and capable of recognizing important patterns even when objects appear in slightly different locations.

The output generated by the pooling layer is then passed to subsequent layers for further processing and feature extraction, contributing to improved classification accuracy and faster model performance.

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Layer 3: Dropout Layer

The Dropout Layer is a regularization technique used in Convolutional Neural Networks (CNNs) to improve the generalization capability of the model and reduce the risk of overfitting. During the training process, a certain percentage of neurons are randomly deactivated or "dropped out" from the network. As a result, these neurons do not participate in forward or backward propagation for that particular training iteration.

By randomly removing neurons, the network is prevented from becoming overly dependent on specific features or connections. This encourages the model to learn more robust and generalized patterns from the training data rather than memorizing it.

The dropout mechanism effectively creates multiple smaller neural networks during training, allowing the model to learn from different combinations of neurons. This improves the model's ability to perform well on unseen data and enhances overall prediction accuracy.

Dropout is typically applied after convolutional or fully connected layers and plays a crucial role in preventing overfitting, especially when working with large and complex neural network architectures. As a result, it contributes to building a more reliable and efficient breast cancer classification system.

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Layer 4: Flatten Layer

The Flatten Layer serves as a bridge between the convolutional layers and the fully connected layers in a Convolutional Neural Network (CNN). After the convolution and pooling operations are completed, the resulting feature maps are typically in a multi-dimensional format. The flattening process converts these feature maps into a one-dimensional vector that can be processed by the dense layers of the network.

The primary purpose of the Flatten Layer is to transform the extracted spatial features into a format suitable for classification. By converting the two-dimensional feature maps into a single continuous vector, the network can efficiently utilize the information learned from previous layers.

During this process, all important local features identified by the convolutional and pooling layers are preserved and combined into a unified representation. This flattened vector is then provided as input to the fully connected layers, where further learning and classification take place.

The Flatten Layer does not perform any mathematical computation or feature extraction itself. Instead, it reorganizes the data structure to enable the transition from feature extraction to decision-making. This step is essential for image classification tasks, as it allows the network to use the learned features to accurately classify input images into their respective categories, such as benign or malignant tumors.

Layer 5: Dense Layer

The Dense Layer, also known as the Fully Connected Layer, is one of the final components of a Convolutional Neural Network (CNN). In this layer, each neuron is connected to every neuron in the preceding layer, allowing the network to combine and interpret the features extracted during the convolution and pooling stages.

The primary function of the Dense Layer is to perform classification based on the information received from the Flatten Layer. It analyzes the extracted features and learns complex relationships between them to make accurate predictions. Through the training process, the weights and biases of the neurons are adjusted to improve the model's performance.

Dense layers are responsible for transforming the learned features into meaningful outputs. In image classification tasks, they help determine the probability of an input image belonging to a particular class. The final dense layer, often referred to as the output layer, generates the classification result, such as identifying whether a breast tumor is benign or malignant.

By combining all the extracted features and performing high-level reasoning, the Dense Layer plays a crucial role in the decision-making process of the CNN model, ultimately contributing to accurate and reliable classification outcomes.

Image recognition by CNN:

The pixels from the image are fed to the convolutional layer that performs the convolution operation. It results in a convolved map. The convolved map is applied to a ReLU function to generate a rectified feature map. The image is processed with multiple convolutions and ReLU layers for locating the features. Different pooling layers with various filters are used to identify specific parts of the image. The pooled feature map is flattened and fed to a fully connected layer to get the final output.

V. CONCLUSION

In a Convolutional Neural Network (CNN), the image classification process begins by feeding the input image into the convolutional layer. The convolution operation applies multiple filters to the image in order to extract important visual features such as edges, textures, patterns, and shapes. The output generated from this process is known as a feature map or convolved feature map.

The generated feature map is then passed through the Rectified Linear Unit (ReLU) activation function, which introduces non-linearity into the network and produces a rectified feature map. Multiple convolutional and ReLU layers are stacked together to progressively extract more complex and meaningful features from the image.

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After feature extraction, pooling layers are applied to reduce the dimensions of the feature maps while retaining the most important information. Pooling helps decrease computational complexity and improves the network's ability to recognize features regardless of their position within the image.

The resulting pooled feature maps are then flattened into a one-dimensional vector using the Flatten Layer. This vector is passed to one or more Fully Connected (Dense) Layers, which analyze the extracted features and perform the final classification.

The final output layer generates the prediction result by assigning the input image to a specific class. In the context of breast cancer detection, the CNN model classifies the image as either **Benign** or **Malignant**, thereby assisting in accurate and automated medical diagnosis.

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