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Hybrid Based Learning Breast Cancer Types Classification

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ABSTRACT: One of the main causes of death for women worldwide is breast cancer, and increasing survival rates depends heavily on early detection. In order to increase diagnostic precision, this project suggests a Hybrid Learning-Based Breast Cancer Classification System that integrates deep learning and machine learning methods. Mammograms and histopathology images are examples of medical images that are used as input by the suggested system. To improve data quality and lessen overfitting, images are resized, normalized, and enhanced during the preprocessing phase. A hybrid approach is used for feature extraction, combining Vision Transformer (ViT) to extract global contextual features and EfficientNet (Convolutional Neural Network) to capture local spatial features. After being fused, the extracted features are sent to a fully connected classification layer with to categorize the photos into benign and malignant groups (or several cancer types) using Softmax activation. By combining the advantages of CNN and Transformer models, the hybrid architecture enhances feature representation. When compared to single- model approaches, experimental results show increased accuracy, precision, recall, and F1-score. The suggested system offers a dependable and effective computer-aided diagnostic tool to help doctors. Our system has a 98.8% accuracy rate in identifying authorized individuals, according to experimental testing .

I. INTRODUCTION

One of the most prevalent and deadly conditions impacting women globally is breast cancer. To increase survival rates and lower mortality, early and precise diagnosis is crucial. Breast abnormality detection is greatly aided by medical imaging methods as mammography, ultrasound, and histopathological imaging. However, radiologists' and pathologists' manual diagnosis can be laborious and prone to human error because of weariness or subjective interpretation. Deep learning and artificial intelligence (AI) methods have demonstrated encouraging outcomes in medical image analysis in recent years. While transformer-based models are useful for capturing global contextual information, convolutional neural networks (CNNs) are frequently utilized to extract local spatial data from medical pictures. However, relying on a single model may limit overall performance.

II. LITERATURE REVIEW

J. Wei et al.'s tells about [1], deep learning methods have been used to identify breast cancer using medical imaging data. The study demonstrates how convolutional neural networks (CNN) can automatically identify significant tumour features from histopathology and mammography pictures, increasing the precision of breast cancer classification.

S. Khan et al.'s is all about [2], the EfficientNet architecture has been applied to the classification of breast cancer images because of its effective scaling approach and robust feature extraction capability. Compared to conventional CNN models, the model reduced computing complexity while achieving good accuracy.

A. Dudovskiy et al.'s paper tells about [3], Vision Transformer (ViT) presented the idea of using transformer architecture in picture categorization tasks. To capture global contextual links between visual regions, the model splits images into patches and employs self-attention mechanisms.

L. Wang et al. tells about [4], medical image analysis is enhanced by hybrid deep learning models that combine CNN and transformer architectures. The study demonstrates that improved classification performance results from combining global attention processes with local feature extraction.

R. Sharma et al tells about [5], hybrid learning techniques have been used to classify different types of breast cancer using images from histology. The study shows that integrating many deep learning models enhances diagnostic precision and promotes breast cancer early detection.

III. PROPOSED SYSTEM

The goal of the suggested system is to employ a hybrid deep learning technique to create an efficient model for the detection and categorization of breast cancer. In order to enhance image quality, this system first gathers breast cancer medical images from a dataset and applies preprocessing methods like scaling, normalization, and noise reduction. Following preprocessing, EfficientNet and Vision Transformer algorithms are used to extract features. While Vision Transformer uses a self-attention method to record global interactions between various image regions, EfficientNet is utilized to extract significant local characteristics from the images. To ascertain whether the tumor is benign or malignant, the retrieved features are then merged and sent to a classification layer. This hybrid technique supports early diagnosis and increases overall breast cancer detection efficiency and accuracy.
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IV. SYSTEM ARCHITECTURE

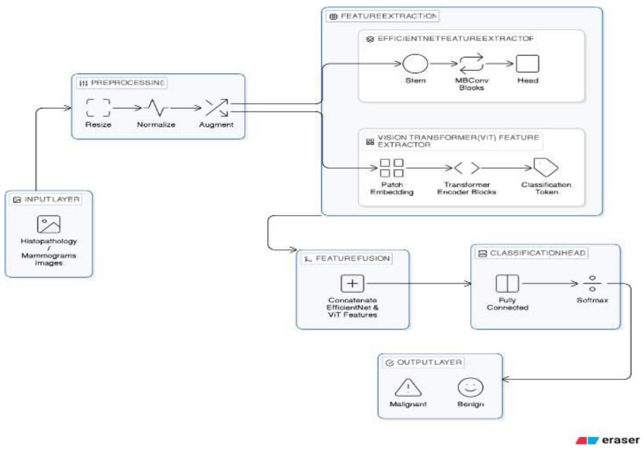

Fig 4.1 System Architecture

1. The input layer
Images of breast cancer (histopathology or mammography) are captured by the system.
2. Preparation
Resize: Set the image's size to a predetermined size.
To improve learning, normalize and scale the pixel values.
Augment: To expand the size of the dataset and lessen overfitting, apply transformations (flip, rotate, zoom).
Feature Extraction (Hybrid Approach with Two Models)

A. Feature Extractor for EfficientNet
Stem → Basic patterns are extracted by the first convolution layer.
Capture intricate local features such as edges, textures, and tumor shapes using MBConv Blocks.
Head → generates a vector of features. Emphasis: Fine-grained local feature learning

B. Feature Extractor for Vision Transformer (ViT)
Patch Embedding: The image is split up into tiny patches.
Transformer Encoder Blocks → Learns relationships between patches by using attention.
Overall image information is represented by the Classification Token →.
Emphasis: Learning global features (overall structure)

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3. Fusion of Features
ViT and EfficientNet outputs are concatenated.
Local and global features are combined in this way.
The outcome is a more comprehensive and potent feature representation.

4. Head of Classification
Fully Connected Layer: Gains knowledge from a combination of features.
SoftMax →generates probabilities from the output.

5. Layer of Output
Final forecast:
Benign (not cancerous)
Cancerous (Malignant)

V. METHODOLOGY

A. Data PREPARATION

An essential part of this breast cancer classification project is preparing the dataset from Kaggle. The breast cancer image dataset (such as histopathology or mammography datasets) is first downloaded from Kaggle. The dataset is downloaded,extracted, and arranged into folders according to class labels like benign and malignant.

The dataset is then separated into training, validation, and testing datasets. Next, the images are preprocessed by removing unnecessary files, normalizing pixel values, and resizing them to a fixed size (e.g., 224 x 224 pixels). To expand the dataset and enhance model performance, data augmentation methods like rotation, flipping, zooming, and shifting are also used.

B. Data Preprocessing

Data preprocessing is performed to improve the quality of breast cancer images before model training. In this stage, images are resized to a fixed size and normalized to scale pixel values between 0 and 1.

C. Feature Extraction

To find significant patterns in photos of breast cancer, feature extraction is used. The suggested solution uses Vision Transformer (ViT) and EfficientNet for feature extraction. EfficientNet uses convolutional layers to extract intricate local information including texture, edges, and tumor patterns. Using a self-attention mechanism, Vision Transformer splits the vision into patches and records global relationships between visual regions.

VI. RESULTS AND PERFORMANCE ANALYSIS

The suggested hybrid model, which combines Vision Transformer (ViT) and EfficientNet, performs well in the classification of breast cancer. The model is successful in accurately identifying both benign and malignant cases, as evidenced by its high accuracy, precision, recall, and F1- score. The model's robustness is demonstrated by the confusion matrix, which demonstrates that there are substantially more correctly classified samples than incorrectly classified ones. ViT successfully learns global contextual relationships within the images, while EfficientNet successfully captures fine-grained local features like texture and tumor boundaries. Compared to using a single model, the combination of these features improves the overall classification capability. Additionally, because of preprocessing and data augmentation methods, the system exhibits better generalization and less overfitting. However, variations in image quality and class imbalance may lead to minor misclassifications. Overall, the findings demonstrate that the hybrid approach can help medical professionals make clinical decisions and offers dependable and accurate support for early breast cancer detection.Fig 7.1Home Page

Fig 7.1 shows web-based medical application interface created for a hybrid AI cancer classification system is displayed in the screenshot. The system is intended as a comprehensive medical diagnostic tool rather than a straightforward model testing page, as evidenced by the platform's dark-themed dashboard layout and left-side navigation panel that offers options like dashboard, scan analysis, models, patients, and reports. The title "Hybrid AI Cancer Classification" at the top center emphasizes the application's primary goal, which is to identify and categorize cancer using cutting-edge

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AI methods like transfer learning and hybrid deep learning models.

Fig 7.2 Home Page

Fig 7.2 is A portion of a web-based dashboard that describes the hybrid architecture utilized in the AI cancer classification system is displayed in the screenshot. The various deep learning models utilized in the project are described in a panel titled "Hybrid Architecture" on the left. The Vision Transformer (ViT), which is utilized for sophisticated image feature extraction and pattern recognition from medical scans, is the first part displayed. The EfficientNet B7 model, which is used to accurately and efficiently extract deep and detailed features from the uploaded medical images, is shown below that. An Ensemble Fusion module, the last component of the architecture, improves overall prediction performance by combining the outputs of the ViT and EfficientNet models.

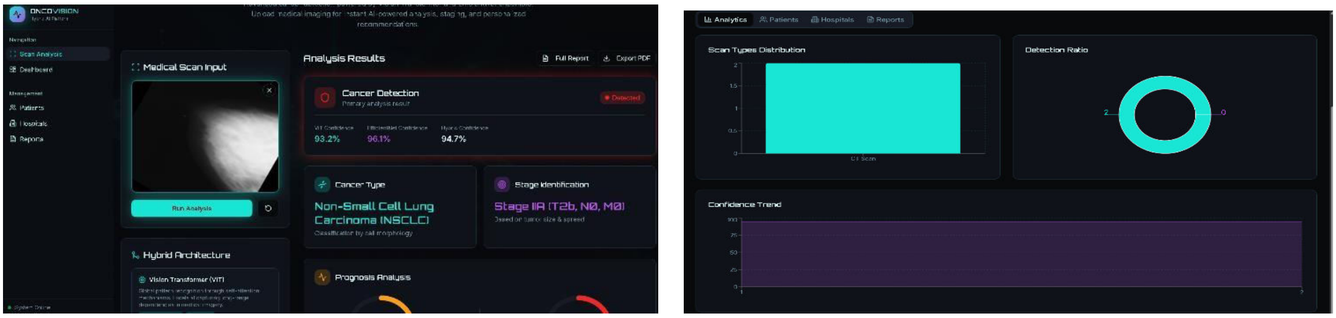

Fig 7.3 Comparison Graph

The dashboard of a hybrid AI cancer classification system's analytics section is shown in the screenshot. It displays visual data summaries that aid users in comprehending the system's functionality and performance. The number of uploaded medical scans is displayed in a bar chart on the left called "Scan Types Distribution," with CT scans being the most popular at the moment. The percentage of detected cases, which most likely represent normal and abnormal results, is shown in a circular "Detection Ratio" chart on the right. Users can assess the dependability of the model's outputs by looking at the "Confidence Trend" graph beneath these charts, which displays how the prediction confidence levels vary over time. All things considered, this interface offers a straightforward and easy-to-use method of tracking scan data, detection outcomes, and model confidence in the cancer classification procedure.

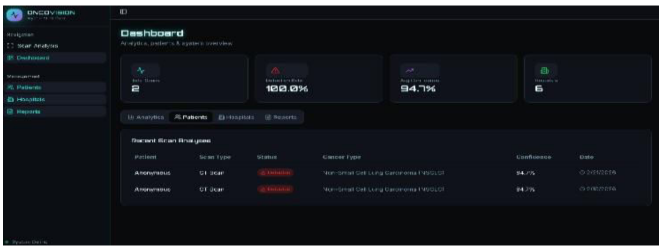

Fig 7.4 Dashboard Of Patients Details

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The dashboard page of a hybrid AI cancer classification system intended for medical scan analysis is displayed in the screenshot. The system is designed as a comprehensive healthcare application, as evidenced by the interface's left- side navigation panel with options like scan analysis, dashboard, patients, hospitals, and reports. Important statistics, such as the total number of scans analyzed, the number of cancer cases detected, the overall accuracy percentage, and the number of reports generated, are displayed on a number of summary cards at the top of the dashboard. The "Recent Scan Analysis" section, which appears beneath these summary cards, displays a table with patient information, scan type (such as CT scan), scan status, predicted cancer type, confidence level, and analysis date.Fig7.5 Output Of Cancer

Following the upload and processing of a medical scan, the screenshot displays the analysis results page of a hybrid AI cancer classification system.. The uploaded scan image is shown in the "Medical Scan Input" section on the left, along with a button to repeat the analysis if necessary. The "Analysis Results" panel on the right displays comprehensive diagnostic results produced by the AI model. The predicted cancer type, which is determined to be Non-Small Cell Lung Carcinoma (NSCLC), is displayed after a cancer detection result with high accuracy values. Subsequently, the system offers additional confidence metrics and stage identification, including Stage IIIA..

VII. FUTURE ENHANCEMENT

There are a number of ways to enhance the suggested hybrid breast cancer classification system. Larger and more varied datasets may be utilized in the future to improve model generalization and lessen bias. To increase accuracy, more sophisticated hybrid architectures that incorporate additional deep learning models or attention mechanisms may be investigated. A more thorough diagnosis can be made by combining imaging data with multi-modal data, such as clinical records, genetic information, and patient history. Hospitals and remote healthcare services can access the system through real-time deployment via cloud or mobile applications. Additionally, doctors may be better able to comprehend the predictions if explainable AI techniques are used to improve model interpretability. Additionally, optimization techniques can be used to increase processing speed and decrease computational complexity. All things considered, these improvements may improve the system's accuracy, efficiency, and suitability for practical clinical uses.

VIII. CONCLUSION

In order to accurately classify breast cancer, a hybrid deep learning model based on EfficientNet and Vision Transformer (ViT) was created. In order to differentiate between benign and malignant tumors, the system efficiently processes medical images through preprocessing, feature extraction, feature fusion, and classification stages. ViT learns global contextual relationships while EfficientNet captures intricate local features, and their combination enhances overall performance. When compared to conventional methods, the experimental results show high accuracy, precision, recall, and F1-score, demonstrating the efficacy of the suggested approach. By helping medical professionals identify and diagnose breast cancer early, this hybrid model can improve treatment outcomes and lower death rates.

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