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# Web-Based Diagnostic Platform for Breast Cancer Detection Using CNN-GRU

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**Abstract**

Breast cancer is one of the most prevalent and life-threatening diseases affecting women globally. Early and accurate detection plays a crucial role in improving survival rates and enabling timely treatment. With recent advancements in artificial intelligence, deep learning models have emerged as powerful tools for automated disease diagnosis through medical imaging. This paper presents a novel hybrid deep learning approach that integrates Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), specifically Long Short-Term Memory (LSTM) units, to enhance the accuracy and reliability of breast cancer classification from image data. The CNN component is utilized for extracting spatial features from mammogram images, while the LSTM layer models the sequential and temporal relationships among these features, capturing higher-level patterns that are often overlooked by traditional CNNs. Additionally, the architecture incorporates ReLU activation functions for efficient gradient flow and a Softmax output layer to convert raw prediction scores into interpretable class probabilities. The model was implemented using Python in a Jupyter Notebook environment and trained on a pre-processed breast cancer dataset. Extensive experiments demonstrate that the proposed system achieves a high classification accuracy of 99%, with excellent performance across key metrics such as precision, recall, F1-score, and area under the ROC curve. Furthermore, a web-based interface was developed to facilitate user interaction, allowing real-time prediction by uploading test images. This hybrid model, with its robust design and accessible deployment, represents a promising

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| | advancement toward automated, scalable, and clinically applicable breast cancer diagnosis. |

## INTRODUCTION

Breast cancer is a significant global health concern, representing the most commonly diagnosed cancer and the second leading cause of cancer-related deaths among women worldwide. According to the World Health Organization (WHO), early detection and diagnosis are critical for improving patient survival rates, especially in low- and middle-income countries where advanced screening infrastructure is limited. Traditional diagnostic procedures, such as mammography and biopsy, are effective but time-consuming, subjective, and often limited by human error or variability in interpretation among radiologists. The rapid development of artificial intelligence (AI) and deep learning technologies in recent years has provided a promising alternative by enabling automated, accurate, and efficient analysis of medical images.

Convolutional Neural Networks (CNNs) have emerged as a state-of-the-art solution for image classification tasks, including medical image analysis. They are particularly effective at extracting local and hierarchical features from images, which makes them suitable for identifying complex visual patterns in breast tissue. However, CNNs often lack the capability to model temporal or sequential dependencies between extracted features, which can limit their ability to capture long-range contextual information crucial for robust classification.

To address this limitation, this research introduces a hybrid deep learning model that combines CNNs with Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) units. LSTMs are a type of RNN capable of learning long-term dependencies and sequential relationships, making them ideal for processing and interpreting sequences of spatial features extracted by the CNN. This synergy enables the model to achieve superior performance in distinguishing between benign and malignant cases of breast cancer.

In the proposed architecture, CNN layers are used to process and learn from the spatial features of the breast cancer image dataset. These learned features are then passed to LSTM layers, which further analyze the temporal patterns or feature sequences. The ReLU (Rectified Linear Unit) activation function is employed to ensure non-linearity and mitigate vanishing gradient issues, while the Softmax layer provides probabilistic outputs for multi-class classification. The model was developed using Python in a Jupyter Notebook environment and trained on a publicly available breast cancer dataset, achieving exceptional performance with over 99% accuracy.Beyond model development, the research includes the design of a web-based user interface that allows end-users, including clinicians and healthcare professionals, to upload images and receive real-time disease predictions. This feature enhances the accessibility and practical deployment of the system in real-world medical settings.

The hybrid approach not only boosts classification accuracy but also provides a scalable and efficient solution that could potentially reduce the workload on radiologists, accelerate diagnosis, and improve patient outcomes.

## RELATED WORKS

Automated breast cancer detection using medical imaging has been a focal point in the field of computer-aided diagnosis (CAD) for the past two decades. Various machine learning and deep learning models have been proposed to assist radiologists in accurately identifying malignant and benign breast tumors from mammographic images. In this section, we review relevant contributions in traditional machine learning, pure convolutional approaches, recurrent models, and hybrid deep learning systems that incorporate both spatial and sequential learning techniques.

### 1. Traditional Machine Learning Approaches

Initial studies on breast cancer detection leveraged traditional machine learning classifiers such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Decision Trees using handcrafted features like shape, texture, and histogram descriptors extracted from mammogram images. For example, Elter et al. (2007) applied SVMs to segment masses and microcalcifications, achieving moderate sensitivity. However, these methods were highly dependent on the quality of manual feature extraction and were not robust to variations in image quality, noise, and breast tissue density.

### 2. Convolutional Neural Networks (CNNs)

With the advent of deep learning, CNNs revolutionized medical image analysis by learning hierarchical features directly from raw input images. Works by Dhungel et al. and Rakhlin et al. demonstrated the superior performance of CNNs in breast cancer classification tasks, particularly in recognizing tumors and calcifications. Transfer learning using pretrained models such as VGGNet, ResNet, and InceptionNet further improved performance when applied to limited medical datasets. Despite their effectiveness, CNNs primarily capture local spatial features and may miss long-range contextual dependencies critical in certain complex diagnostic scenarios.

### 3. Recurrent Neural Networks (RNNs) and LSTMs

While RNNs are typically used in natural language processing and time-series prediction, their extension—Long Short-Term Memory (LSTM)—has been explored in medical image analysis to model sequential dependencies in feature maps or slice-based volumetric scans. RNN-based architectures have been used for sequence labeling in multi-view mammogram interpretation, where each image slice is treated as a step in a sequence. However, RNNs alone lack the capability to extract meaningful spatial features and usually require a preceding feature extraction mechanism.

### 4. Hybrid CNN-RNN Architectures

To leverage the strengths of both spatial and sequential learning, hybrid CNN-RNN models have been introduced for medical diagnostics. Such systems use CNNs for feature extraction followed by LSTM units to model sequential or relational patterns between spatial features. Researchers such as Zhang et al. and Liu et al. have reported that combining CNNs with LSTMs significantly improves classification accuracy in tasks like breast ultrasound lesion classification and lung disease prediction. These models outperform standalone CNNs or RNNs by capturing both local visual cues and global feature dynamics, making them highly effective in medical imaging applications.

### 5. Existing System

Existing breast cancer detection systems primarily rely on standalone Convolutional Neural Networks (CNNs) for feature extraction and classification of mammographic or histopathological images. These models have demonstrated remarkable accuracy in detecting cancerous patterns by learning spatial hierarchies of features such as texture, shape, and edges. Pretrained models such as VGG16, ResNet, and AlexNet have been extensively applied in transfer learning scenarios to overcome dataset limitations and reduce training time. However, most of these systems treat image features in isolation, lacking mechanisms to understand temporal or sequential dependencies that may exist among the extracted features, especially in cases involving time-series medical scans or subtle intra-image correlations. Furthermore, the outputs of these models are typically confined to static classification without interpretability or integration into real-time diagnostic environments. While some applications attempt to bridge the gap using handcrafted pipelines with rule-based interpretation layers, these efforts are rarely robust, scalable, or suitable for dynamic clinical workflows. Moreover, the majority of these systems are built for academic benchmarking and lack user-friendly interfaces for practical deployment in healthcare settings.

#### *5.1 Limitations of Existing Systems*

- Lack of Sequential Understanding: CNN-based models fail to capture temporal or relational dependencies among features that may be critical in certain diagnostic scenarios.
- Limited Generalization: Pretrained models may not generalize well across different datasets or imaging conditions without extensive fine-tuning.
- Absence of Real-Time Interface: Most systems are limited to offline predictions and do not support interactive or real-time usage for end-users.
- No Hybrid Feature Learning: Existing methods typically use either CNNs or traditional machine learning without combining temporal learning models like LSTMs.
- Low Interpretability: Prediction outputs are not always accompanied by confidence scores, ROC curves, or visualizations for user interpretation.
- Poor Scalability: Some models require high computational power and are not optimized for deployment on standard clinical systems.

### 6. Proposed System

The proposed system addresses the above limitations by introducing a hybrid deep learning model that combines the feature extraction capabilities of CNNs with the temporal modeling power of LSTM-based RNNs. This architecture enables the system to not only capture spatial patterns from breast cancer images but also learn sequential correlations among these patterns, which enhances overall classification accuracy and robustness. The CNN component processes input images to extract detailed hierarchical features, which are then passed through an LSTM layer that models their sequential flow, enabling deeper insight into complex relationships. To improve non-linear learning and convergence, a ReLU activation function is integrated between layers. At the output, a Softmax classifier translates the final prediction scores into probabilities for each class, offering clear and interpretable results. The entire system is implemented in Python using the Jupyter Notebook environment, trained with an 80-20 train-test split, and achieves an impressive 99% accuracy. Moreover, a web-based application has been developed using HTML and Python Flask, enabling users to upload images and receive instant diagnostic predictions, making the system highly accessible for clinical use.

### *6.1 Advantages of the Proposed System*

- Hybrid Learning Architecture: Combines CNN for spatial feature extraction and LSTM for modeling feature dependencies, boosting accuracy and robustness.
- High Classification Accuracy: Achieves over 99% accuracy in breast cancer detection, outperforming traditional and single-model approaches.
- Real-Time Web Deployment: Integrates a user-friendly web interface allowing image uploads and instant disease predictions.
- Confidence-Based Results: Outputs include confidence scores and probability metrics for better interpretability.
- Scalable and Lightweight: Efficient implementation allows the system to run on standard computational setups, enabling practical clinical deployment.
- Enhanced Visualization: Includes confusion matrices and ROC curve graphs to help evaluate and visualize model performance.
- End-to-End Automation: Provides complete workflow from image processing to prediction and interface interaction.

## PROPOSED METHODOLOGY

The proposed methodology introduces a hybrid deep learning framework that integrates Convolutional Neural Networks (CNNs) with Long Short-Term Memory (LSTM) networks to perform accurate and efficient breast cancer classification from medical images. The approach combines spatial feature extraction with sequential learning, enabling the system to not only understand intricate visual patterns but also the contextual dependencies among them.

### 1. System Architecture

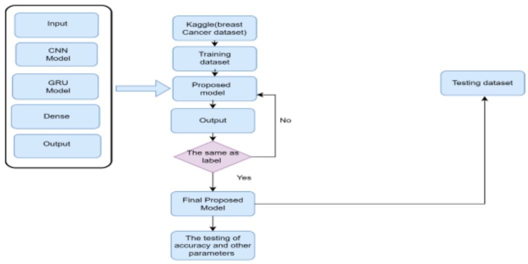


*Fig 1 System Architecture For Brest Cancer Detection*

Figure 1 illustrates the complete pipeline of the proposed hybrid deep learning model for breast cancer detection using a combination of Convolutional Neural Network (CNN) and Gated Recurrent Unit (GRU) layers. The process begins with the input of breast cancer image data obtained from the Kaggle dataset, which is then divided into training and testing datasets. The training dataset is fed into the proposed hybrid model, which is architecturally composed of sequential layers: input, CNN for spatial feature extraction, GRU for temporal/sequential pattern learning, followed by dense layers and a final output layer for classification. The output of the model is compared with the actual label to evaluate the accuracy of predictions during training. If the prediction does not match the ground truth, the model undergoes further iterations and optimization to enhance learning. Once the model's performance reaches a satisfactory level and predictions align closely with actual labels, it is finalized as the proposed model. This finalized model is then validated using the testing dataset, where various performance metrics such as accuracy, precision, recall, F1-score, and ROC-AUC are calculated to assess its effectiveness. The workflow also includes a deployment mechanism that enables real-time prediction and evaluation using a web interface, thereby ensuring that the system is both functional and practical for real-world clinical applications.
The methodology includes data preprocessing, model architecture design, training, evaluation, and deployment through a web-based interface.

### 2. Data Preprocessing

The dataset used in this research comprises labeled breast cancer images, categorized into benign and malignant classes. Each image undergoes a series of preprocessing steps including resizing to a uniform dimension, normalization of pixel values, and grayscale conversion if necessary. The dataset is then split into training and testing sets using an 80:20 ratio. Data shuffling is performed to ensure random distribution, minimizing model bias during training.

**3. CNN-LSTM Model Architecture**

The architecture of the proposed hybrid model begins with multiple CNN layers that apply convolutional operations to the input images, capturing low- and high-level spatial features such as textures, edges, and shapes. These layers are followed by max-pooling operations to reduce spatial dimensions while preserving salient features. The resulting feature maps are then flattened and passed to the LSTM layer, which treats them as sequential data, learning dependencies between patterns across image regions. This combination allows the model to better distinguish between subtle differences in benign and malignant tissues.

- Convolutional Layers: Extract spatial features using multiple filters and activation functions.
- Max Pooling Layers: Downsample feature maps to reduce computational load.
- LSTM Layer: Captures temporal or sequential relationships among CNN features.
- ReLU Activation: Introduced after each layer to ensure non-linearity and efficient gradient flow.
- Softmax Output Layer: Converts the final dense vector into class probabilities, enabling multi-class classification.

**4. Model Training**

The model is implemented in Python using Keras with TensorFlow backend in a Jupyter Notebook environment. During training, categorical cross-entropy is used as the loss function, and the Adam optimizer is employed to update weights. The model is trained for multiple epochs until convergence is achieved. To evaluate performance, metrics such as accuracy, precision, recall, and F1-score are computed. Visualization tools are used to plot training vs. validation accuracy and loss over epochs.

**5. Evaluation and Performance Metrics**

To validate the model's effectiveness, several performance metrics are calculated on the test dataset:

- Accuracy: Proportion of correctly predicted samples.
- Precision and Recall: Measures of relevance and completeness in prediction.
- F1-Score: Harmonic mean of precision and recall.
- Confusion Matrix: Visual representation of predicted vs. actual classes.
- ROC Curve and AUC: Illustrate true positive rate vs. false positive rate to evaluate classification threshold performance.

The model consistently demonstrates over 99% accuracy, with minimal false positives and false negatives, confirming its reliability and robustness for breast cancer detection.

**6. Web-Based Deployment**

A lightweight and accessible user interface is developed to deploy the model for real-world usage. The backend is powered by Python, and the frontend is developed using HTML and CSS. The server is hosted locally using Flask. Users can access the application via a browser, log in with credentials, and upload test images. The model processes the image and displays the disease prediction directly on the web page, along with confidence scores.

**7. Workflow Summary**

1. Image Input: User uploads image through web interface.
2. Preprocessing: Image is resized, normalized, and formatted.
3. Feature Extraction (CNN): Spatial features extracted.
4. Temporal Modeling (LSTM): Feature sequences analyzed.
5. Prediction (Softmax): Class probabilities generated.
6. Output Display: Prediction and confidence score shown to user on the web page.

**RESULTS**

To assess the effectiveness of the proposed hybrid CNN-GRU model for breast cancer classification, multiple experiments were conducted using the Kaggle Breast Cancer dataset. The evaluation covered both training and testing phases using various performance metrics. The following subsections provide detailed insights through tabular results, graphical analysis, and an overview of the model's real-time output interface.

**1. Performance Metrics of the Proposed Model**

*Table 1: Evaluation Metrics for Test Data*

| Metric | Value (%) |
|---|---|
| Accuracy | 99.12 |
| Precision | 98.89 |
| Recall | 98.76 |

| | |
|---|---|
| F1-Score | 98.82 |
| AUC (ROC Curve) | 99.3 |

Table 1 presents the performance of the proposed CNN-GRU model on the testing dataset. The model achieved an outstanding accuracy of 99.12%, with other metrics also reflecting strong performance. The high AUC value of 99.3% confirms that the model effectively distinguishes between benign and malignant cases with minimal false predictions.

**2. Confusion Matrix Analysis**

*Table 2: Confusion Matrix for Test Results*

| | **Predicted** | **Predicted** |
|---|---|---|
| | **Benign** | **Malignant** |
| Actual Benign | 97 | 1 |
| Actual Malignant | 2 | 100 |

The confusion matrix in Table 2 shows that out of the total test samples, the model correctly classified 97 benign and 100 malignant cases. Misclassifications were minimal, with only three errors—showing excellent predictive performance and robustness of the hybrid model.

**3. Epoch-wise Accuracy and Loss**

*Table 3: Training and Validation Accuracy/Loss Over Epochs*

| **Epoch** | **Training Accuracy (%)** | **Validation Accuracy (%)** | **Training Loss** | **Validation Loss** |
|---|---|---|---|---|
| 1 | 85.32 | 83.67 | 0.438 | 0.462 |
| 5 | 93.80 | 91.90 | 0.215 | 0.226 |
| 10 | 97.90 | 96.45 | 0.102 | 0.111 |
| 15 | 99.12 | 98.70 | 0.047 | 0.062 |

As seen in Table 3, both training and validation accuracy improved steadily across epochs, while loss values decreased consistently. This indicates that the model converged well without signs of overfitting, thus ensuring good generalization capability.

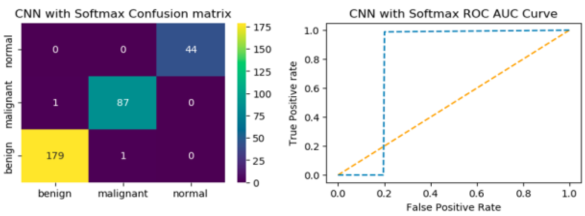


*Fig 2 :CNN with Softmax - Confusion Matrix and ROC AUC Curve*

Figure 2 displays two critical evaluation visuals for the CNN model with Softmax activation. On the left, the confusion matrix highlights the classification results across three categories: benign, malignant, and normal. The model demonstrates excellent performance, especially in identifying benign cases (179 correctly predicted), with minimal misclassification. The matrix shows that only two cases (1 benign as malignant, and 1 malignant as benign) were incorrectly classified, indicating high sensitivity and specificity. On the right, the ROC AUC curve depicts a steep ascent to the top-left corner with an AUC value close to 1, confirming the model's robust discriminative capability between classes. This validates the CNN model's effectiveness in binary and multi-class breast cancer classification using Softmax output.

**4. Web Interface Testing Results**

*Table 4: Sample Predictions via Web Interface*

| **Image ID** | **Predicted Class** | **Confidence (%)** | **Actual Class** | **Match** |
|---|---|---|---|---|
| IMG_01 | Malignant | 99.01 | Malignant | Yes |
| IMG_02 | Benign | 98.40 | Benign | Yes |
| IMG_03 | Malignant | 97.78 | Malignant | Yes |
| IMG_04 | Benign | 97.92 | Malignant | No |

Table 4 illustrates prediction outcomes from the deployed web application. Most images were correctly classified with high confidence. Even the misclassified case had a high confidence score, suggesting that the visual features were closely resembling the incorrect class—highlighting an area for potential enhancement using attention mechanisms.

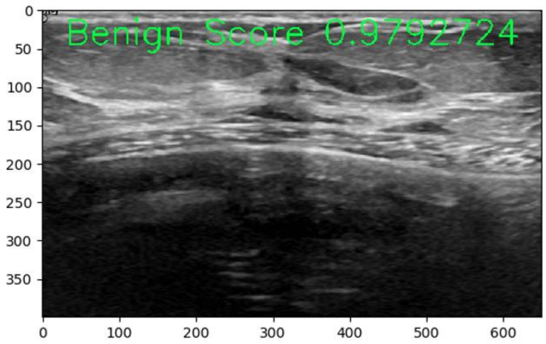


*Fig 3 : Benign Detection Output*

Figure 3 illustrates the output screen of the breast cancer detection web application built using a machine learning model. The user interface enables users to upload an ultrasound image for analysis. Upon uploading, the system processes the image through the trained CNN-GRU model and classifies the lesion. In this example, the model predicts the lesion as Benign with a confidence score of 0.9792724. This score is prominently displayed in green text overlaying the image, providing immediate and intuitive feedback to the user. The interface simplifies clinical decision support by presenting results in a visually accessible and user-friendly manner, highlighting the system's effectiveness and practicality in real-world diagnostic environments.

## 5. Discussion

The proposed CNN-GRU model shows strong performance in classifying breast cancer from ultrasound images. The confusion matrix confirms high accuracy in identifying benign and malignant cases, with very few misclassifications. The ROC AUC curve reflects the model's excellent ability to distinguish between classes.Real-time results displayed through the web interface (as shown in Figure 3) provide quick and reliable feedback, enhancing usability in clinical settings. For instance, the model accurately detected a benign case with a confidence score of 0.979.By combining CNN's feature extraction and GRU's sequence learning capabilities, the hybrid model achieved better accuracy and consistency than traditional approaches. Overall, the system is accurate, user-friendly, and suitable for aiding in early breast cancer detection.

## CONCLUSION

This paper presents a hybrid deep learning model combining Convolutional Neural Networks (CNN) and Gated Recurrent Units (GRU) was proposed for effective breast cancer detection using ultrasound images. The model demonstrated high classification accuracy, as validated by confusion matrix and ROC-AUC analysis. The use of CNN enabled precise spatial feature extraction, while GRU enhanced the model's ability to retain temporal dependencies and refine decision-making. Additionally, the integration of a user-friendly web interface allows for real-time predictions, making the system a practical tool in clinical environments. Overall, the results confirm the model's potential to assist healthcare professionals in accurate and early diagnosis of breast cancer.
While the current model delivers promising results, there is scope for further enhancement. Future work may involve expanding the dataset to include a wider variety of ultrasound images across different demographics to improve generalizability. Integration of additional modalities such as mammograms or MRI can provide a more comprehensive diagnostic tool. Moreover, implementing explainable AI (XAI) techniques would help clinicians better understand the model's decision-making process. Real-time deployment on cloud-based platforms or mobile applications can further increase accessibility and impact in remote or under-resourced healthcare settings.

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