First Review

On

Early Detection and Classification of Breast Cancer from Mammograms

Submitted by:

Laxmi Sai. G (21MIS7119)

Vasudha Rani. P (21MIS7121)

To

Dr. B.V. Gokulnath

School Of Computer Science and Engineering (SCOPE)

Beside AP Secretariat, Near Vijayawada, Amaravati, Andhra Pradesh, India, 522237

SYSTEM REQUIRMENT SPECIFICATIONS

PURPOSE OF THE PROJECT:

Breast cancer is the most frequently occurring cancer in women and is characterized by the uncontrolled growth of abnormal breast cells that form tumors. If not identified and treated early, these tumors can spread throughout the body and become fatal. Early detection is critical to improving treatment outcomes and survival rates. Utilizing a CLAHE-enhanced mammogram dataset from Kaggle, the model aims to accurately classify images into the three categories: Benign, Malignant, and Normal. We propose a hybrid model that combines Convolutional Neural Networks (CNNs) and Vision Transformers (Vits). By integrating CNNs for local feature extraction and ViTs for global context integration, our approach seeks to improve the early detection and diagnosis of breast cancer, ultimately aiding in timely treatment and reducing mortality rates.

PROBLEMS IN THE EXISTING MODELS:

- CNNs are highly effective at capturing local features due to their convolutional layers but may struggle with capturing long-range dependencies.
- ViTs often require large amounts of data and computational power to train effectively, as they lack the inherent inductive biases of CNNs.
- YOLO models are effective for object detection but can struggle with fine-grained classification tasks and feature extraction from medical images.
- While Efficient Net is designed for high performance with fewer parameters, it may still miss out on capturing long-range dependencies and global context.
- Some models are designed for image segmentation but may have limitations in handling complex and varied datasets, particularly in medical imaging where the structures can be subtle and varied.

SOLUTION OF THESE PROBLEMS:

Solutions Using Hybrid Model of CNN and Pre-trained ViT:

1. Local Feature Extraction and Long-Range Dependencies: Use CNN layers to extract detailed local features and feed them into pre-trained ViT layers to capture long-range dependencies and global context.

2. Data and Computational Requirements of ViTs: Pre-trained ViTs can reduce the data and computational requirements. Use a CNN backbone to preprocess the image, providing a compact representation to the ViT.

3. Fine-Grained Classification and Feature Extraction: Employ CNNs for initial object detection and fine-grained feature extraction, and then use ViT layers to enhance classification by understanding the broader context.

4. Complex and Varied Datasets in Image Segmentation: Utilize CNNs for detailed segmentation of local structures and use ViT layers to handle the global structure and variations within the medical images.

SCOPE OF THE PROJECT:

The scope of implementing this hybrid CNN-ViT model for mammogram classification is multifaceted. Firstly, it aims to enhance the accuracy and reliability of identifying breast abnormalities, crucial for early detection and prompt medical intervention. By leveraging CNNs for local feature extraction and ViTs for comprehensive global context understanding, the model can potentially improve upon traditional approaches that rely solely on either local or global information. This approach not only supports radiologists in making more informed decisions but also contributes to the broader goal of reducing false positives and negatives in breast cancer screening. Moreover, the integration of advanced deep learning techniques like ViTs into medical imaging underscores the potential for innovative applications in healthcare, paving the way for more sophisticated diagnostic tools and improving patient outcomes through earlier and more accurate diagnoses.

FUNCTIONAL COMPONENTS OF PROJECT:

1. **Data Preprocessing:**
   - **Dataset Utilization:** Using the CLAHE-enhanced mammogram dataset directly obtained from Kaggle for training and evaluation purposes.
   - **Data Augmentation:** Applying augmentation techniques (e.g., rotations, flips, zooms) to increase dataset diversity and improve model robustness.

Feature Extraction:

2. **CNN Layers with Pooling:**
   - **Convolutional Layers:** The model employs multiple convolutional layers for initial feature extraction from mammogram images. These layers use learnable filters to detect local patterns and structures that are crucial for breast cancer diagnosis.
   - **Pooling Layers:** Following each convolutional layer, pooling layers (e.g., MaxPooling2D) are used to down sample the feature maps. Pooling helps reduce the spatial dimensions of the feature maps while retaining important information, enhancing computational efficiency and reducing overfitting.
3. **Input to Vision Transformer (ViT):**
   - **Output Feature Map:** The output of the last pooling layer serves as the input to the Vision Transformer (ViT) component of the model. This feature map encapsulates localized

features extracted by the CNN layers and is essential for capturing detailed information relevant to breast abnormalities.

4. **Model Architecture:**
   - **Integration of Vision Transformers (ViTs):** Incorporating pre-trained ViT layers into the model to capture long-range dependencies and global context across the entire mammogram image.
   - **TensorFlow and Keras Frameworks:** Utilizing these frameworks for model development, training, and deployment, leveraging their comprehensive tools and libraries for deep learning tasks.
5. **Training and Optimization:(optional)**
   - **Transfer Learning:** Fine-tuning pre-trained CNN and ViT models on the CLAHE-enhanced mammogram dataset to optimize model performance and accelerate convergence.
   - **Hyperparameter Tuning:** Iteratively adjusting model parameters (e.g., learning rate, batch size) using TensorFlow and Keras APIs to maximize classification accuracy and efficiency.
6. **Evaluation and Validation:**
   - **Performance Metrics:** Evaluating model performance using standard metrics (accuracy, precision, recall, F1-score) to assess its effectiveness in classifying mammograms into Benign, Malignant, and Normal categories.
   - **Cross-Validation:** Implementing cross-validation techniques within TensorFlow/Keras pipelines to validate model robustness and generalization across different dataset partitions.
7. **Monitoring and Maintenance:**
   - **Performance Monitoring:** Implementing continuous monitoring mechanisms to track model performance post-deployment, including drift detection and retraining strategies using TensorFlow/Keras tools.
   - **Model Updates:** Incorporating updates based on new data or advancements in deep learning methodologies to enhance diagnostic accuracy and clinical utility over time.

By integrating these components, the project aims to develop an advanced tool for accurate and timely breast cancer detection, leveraging the strengths of CNNs, ViTs, and TensorFlow/Keras frameworks to improve patient outcomes and healthcare efficiency.

STUDY OF THE MODEL:

Convolutional Neural Network (CNN):

Working of CNN:

- **Convolutional Layers:** These layers consist of learnable filters (kernels) that slide over input images to extract local patterns such as edges, textures, and shapes. Each filter produces a feature map that highlights specific features from the input.

- **Pooling Layers:** Following convolutional layers, pooling layers (e.g., MaxPooling2D) downsample the feature maps by summarizing information within local patches. This reduces the spatial dimensions of the features while preserving their essential information.
- **Activation Functions:** Layers often include activation functions like ReLU (Rectified Linear Unit) to introduce non-linearity, enhancing the model's ability to learn complex patterns.

Vision Transformer (ViT):

Working of ViT:

- **Patch Embeddings:** The input image is divided into fixed-size patches, which are then linearly embedded into lower-dimensional vectors. These embeddings preserve spatial relationships and facilitate parallel processing of image patches.
- **Transformer Encoder:** These layers process the embeddings using multi-head self-attention mechanisms and position-wise feedforward networks. Self-attention enables each patch to attend to all other patches, capturing global dependencies and context.
- **Classification Head:** The final transformer output is typically used for classification tasks, where a linear layer and softmax activation function classify the input image into predefined classes.

Hybrid Model Architecture (CNN-ViT):

Combined Architecture:

- **Feature Extraction:** Initially, CNN layers (convolutional and pooling) are used to extract detailed local features from mammogram images. These features capture specific patterns and structures indicative of breast abnormalities.
- **Integration with ViT:** The output feature maps from the CNN layers serve as input to the Vision Transformer. This integration allows the Vit to capture long-range dependencies and global context across the entire image, leveraging the detailed local features extracted by CNNs.
- **Fine-Tuning:** The combined CNN-Vit architecture is fine-tuned on the CLAHE-enhanced mammogram dataset using transfer learning. This process adjusts model parameters to better fit the specific characteristics of the dataset, enhancing classification performance without starting training from scratch.

Benefits of Hybrid Approach:

- **Comprehensive Information Utilization:** By combining CNNs and Vit's, the model leverages the strengths of both architectures: CNNs for local feature extraction and Vit's for capturing global context, resulting in more accurate and robust classification of mammogram images.

- **Enhanced Diagnostic Capabilities:** The hybrid model's ability to integrate local and global information can potentially improve early detection and diagnosis of breast cancer, aiding healthcare professionals in making informed decisions.

In summary, the hybrid CNN-Vit model for mammogram classification offers a synergistic approach to leveraging deep learning techniques for medical imaging analysis. It harnesses the complementary strengths of CNNs and Vits, enhanced through fine-tuning on specific datasets, to advance the accuracy and efficacy of breast cancer detection and diagnosis.

PERFORMANCE REQUIREMENTS:

Performance Measures:

1. **Accuracy:** Achieve high overall accuracy in classifying mammogram images into Benign, Malignant, and Normal categories. The accuracy metric indicates the percentage of correctly classified images out of the total.
2. **Precision:** Ensure high precision in identifying each class (Benign, Malignant, Normal). Precision measures the percentage of correctly predicted positive instances (true positives) relative to all instances predicted as positive (true positives + false positives).
3. **Recall (Sensitivity):** Achieve high recall for each class, particularly for Malignant cases. Recall measures the percentage of correctly predicted positive instances (true positives) relative to all actual positive instances (true positives + false negatives).
4. **F1-Score:** Maintain a high F1-score to balance between precision and recall for each class. The F1-score is the harmonic mean of precision and recall and provides a single metric to assess a model's overall performance.
5. **Confusion Matrix Analysis:** Analyze the confusion matrix to understand the distribution of predicted and actual class labels. Identify and minimize misclassifications, particularly false positives and false negatives, which are critical in medical diagnosis.

Requirements:

1. **High Accuracy:** The model must achieve a high overall accuracy to reliably classify mammogram images, minimizing misdiagnoses and ensuring patient safety.
2. **Balanced Precision and Recall:** To effectively identify breast abnormalities, the model needs balanced precision and recall across all classes, with a particular focus on detecting Malignant cases.
3. **Robustness to Imbalanced Data:** Given that medical datasets often exhibit class imbalance (e.g., fewer Malignant cases compared to Benign or Normal), the model should handle imbalanced data effectively to prevent biases in performance metrics.
4. **Generalization:** The model should generalize well to unseen mammogram images from diverse sources, ensuring its applicability in real-world clinical settings beyond the training dataset.

By focusing on these performance measures and requirements, the project aims to develop a robust and clinically relevant tool for breast cancer detection and diagnosis, leveraging the strengths of hybrid CNN-Vit architecture and deep learning methodologies.

FEASIBILITY REPORT:

Introduction:

- **Project Overview:** The project aims to develop a hybrid deep learning model combining Convolutional Neural Networks (CNNs) and Vision Transformers (Vit's) for classifying mammogram images into Benign, Malignant, and Normal categories.
- **Objectives:** Enhance early detection of breast abnormalities to improve diagnosis accuracy and patient outcomes.

Executive Summary:

- The feasibility study assesses the technical, financial, and operational aspects of implementing the CNN-Vit model for mammogram classification.
- Key findings highlight the project's potential to significantly impact breast cancer detection through advanced deep learning techniques.

Technical Feasibility:

- **Model Architecture:** Integration of CNN layers for local feature extraction and Vit layers for capturing global context is technically feasible using TensorFlow and Kera's frameworks.
- **Data Requirements:** Availability of a CLAHE-enhanced mammogram dataset from Kaggle meets project needs, though data augmentation may be necessary to address potential class imbalance.

Financial Feasibility:

- **Cost Analysis:** Costs include computing resources (e.g., GPU for model training), software licenses (TensorFlow/Kera's), and potential costs associated with data acquisition and augmentation.

Operational Feasibility:

- **Deployment Strategy:** Plan for integrating the CNN-Vit model into existing healthcare systems or as a standalone diagnostic tool. (optional)
- **Scalability:** Considerations for scaling model deployment to handle increased data volumes and future enhancements.

Legal and Regulatory Considerations:

- **Data Privacy:** Compliance with medical data privacy regulations (e.g., HIPAA) ensures secure handling of patient information and informed consent for data usage.

Risk Assessment:

- **Technical Risks:** Potential challenges include model overfitting, convergence issues during training, and computational resource limitations.
- **Data Risks:** Addressing data quality issues, potential biases in dataset annotations, and ensuring robustness against variations in mammogram imaging techniques.

Environmental and Social Impact:

- **Environmental Considerations:** Minimal environmental impact due to computational requirements, with potential positive societal impact through improved healthcare outcomes.
- **Social Implications:** Enhancing breast cancer detection contributes to public health initiatives, potentially reducing mortality rates and improving quality of life for patients.

Conclusion and Recommendations:

- **Feasibility Assessment:** The project is deemed feasible based on technical capabilities, available resources, and alignment with regulatory requirements.
- **Recommendations:** Proceed with model development, emphasizing rigorous testing, validation against clinical standards, and continuous monitoring of performance metrics.
- **Next Steps:** Initiate pilot testing in collaboration with medical professionals to validate model effectiveness and refine deployment strategies for broader implementation.

MODEL DESIGN / ARCHITECTURAL DIAGRAM: