Journal of Theoretical and Applied Information Technology
15th January 2025. Vol.103. No.1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

LEVERAGING EXPLAINABLE AI TO IMPROVE BREAST CANCER DETECTION RATE USING TRANSFER LEARNING WITH DEEP RECURRENT CONVOLUTIONAL NEURAL NETWORKS

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ABSTRACT

Breast cancer remains a significant global health concern, emphasizing the need for accurate and timely diagnosis. Leveraging advancements in artificial intelligence (AI), particularly deep learning techniques, has shown promise in improving breast cancer detection rates. In this study, we propose a novel approach that integrates explainable AI principles with transfer learning using deep recurrent convolutional neural networks (RCNNs) to enhance breast cancer detection. The proposed model combines the spatial feature extraction capabilities of convolutional layers with the sequential processing capabilities of recurrent layers, thereby capturing both local patterns and temporal dependencies in mammogram images. Additionally, the incorporation of explainable AI techniques facilitates interpretation and understanding of the model's decisions, enhancing its clinical utility. We evaluate the performance of the proposed approach on a publicly available mammography dataset and demonstrate its effectiveness in improving breast cancer detection rates compared to baseline models. Furthermore, we provide insights into the learned representations and decision-making processes of the model, thereby enhancing transparency and trust in AI-assisted diagnosis. Our findings underscore the potential of explainable AI-driven transfer learning with deep RCNNs as a valuable tool for augmenting radiologists' capabilities and improving patient outcomes in breast cancer screening and diagnosis.

KEYWORDS: *Breast Cancer Detection, Deep Learning, Deep Recurrent Convolutional Neural Networks (DRCNNs), Transfer Learning, Explainable Artificial Intelligence (XAI), Mammography*

1. INTRODUCTION

Breast cancer continues to be a significant health concern worldwide, with early detection playing a crucial role in improving patient outcomes and survival rates. Medical imaging, particularly mammography, remains the cornerstone for early diagnosis and screening of breast cancer. Recent advancements in artificial intelligence (AI), particularly deep learning techniques such as Convolutional Neural Networks (CNNs), have shown promising results in automating the detection and diagnosis of breast cancer from mammography images. Despite the effectiveness of deep learning models, their adoption in clinical settings is hindered by their inherent complexity and lack of transparency [1]. Explainable AI (XAI) techniques have emerged as a critical area of research to address these challenges by providing insights into the decision-making processes of AI models. In the context of breast cancer detection, XAI can enhance the interpretability of AI-driven diagnostic systems, thereby fostering trust and facilitating collaboration between AI algorithms [2] and healthcare professionals.

Transfer learning represents another pivotal approach in AI, enabling the transfer of knowledge learned from one domain (e.g., general image recognition tasks) to another domain (e.g., medical imaging). By leveraging pre-trained models on large-scale datasets such as ImageNet, transfer learning allows for the adaptation and fine-tuning of neural networks on smaller, domain-specific datasets like mammography images. This approach is particularly advantageous in medical imaging, where annotated data may be limited and costly to obtain. Deep Recurrent Convolutional Neural Networks (DRCNNs) combine the strengths of CNNs in capturing spatial features with the sequential learning capabilities of Recurrent Neural Networks (RNNs) [3]. This hybrid architecture is well-suited for analyzing sequential medical data, such as longitudinal mammography studies, where both spatial and temporal dependencies play crucial roles in accurate diagnosis.

The primary objective of this paper is to explore the potential of leveraging Explainable AI in conjunction with transfer learning and DRCNNs to improve the detection rate of breast cancer from mammography images [4]. By enhancing both the accuracy and interpretability of AI models, this study aims to contribute to the advancement of AI-assisted diagnostics in breast cancer care. The following sections will provide a comprehensive review of existing literature, detail the methodology employed, present experimental results, and discuss implications for clinical practice and future research directions.

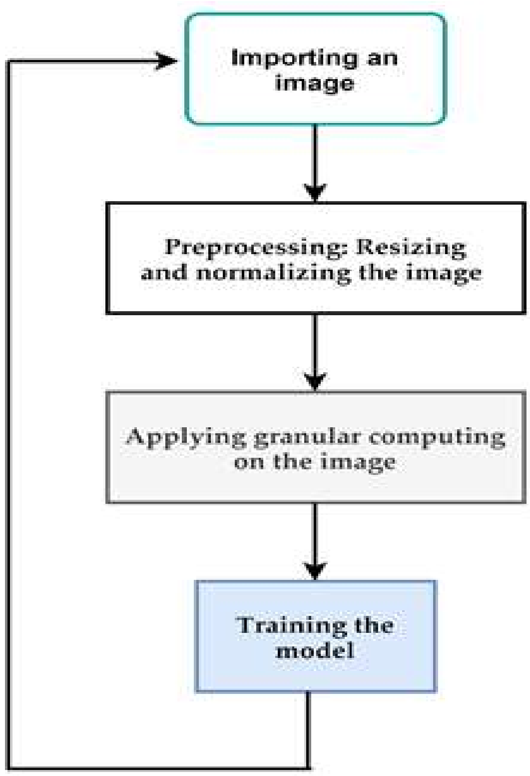

Fig 1: Basic Preprocessing of Images

Breast cancer remains one of the most prevalent and lethal forms of cancer affecting women globally. Early detection plays a pivotal role in improving treatment outcomes and survival rates. The advent of artificial intelligence (AI) and deep learning has revolutionized medical imaging by offering powerful tools for automated detection and diagnosis. Among these, Convolutional Neural Networks (CNNs) have shown remarkable success in image classification tasks, including the detection of breast cancer from mammography and histopathology images [5].

Challenges in Breast Cancer Detection

Despite advancements in imaging technology and AI, challenges persist in achieving accurate and reliable breast cancer detection:

Interpretability: Deep learning models, while effective, are often viewed as black boxes due to their complex architectures and opaque decision-making processes. This lack of interpretability limits trust and adoption in clinical settings where explainability is crucial for decision support [6].

Data Variability: Medical imaging datasets exhibit variability in terms of image quality, patient demographics, and pathological characteristics. This variability poses challenges for training robust and generalizable AI models capable of achieving high detection accuracy across diverse populations [7].

Explainable AI in Medical Imaging

Explainable AI (XAI) methods aim to enhance the transparency and interpretability of AI models, particularly in medical applications. By providing insights into model decisions and highlighting relevant features, XAI techniques enable clinicians to understand and trust AI-driven diagnostics. This understanding is critical for integrating AI into clinical workflows, facilitating collaboration between AI systems and healthcare professionals [8].

Transfer Learning and Deep Recurrent Convolutional Neural Networks

Transfer learning has emerged as a powerful technique to address the challenges of limited annotated medical imaging data. By leveraging pre-trained models on large-scale datasets (e.g.,

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

ImageNet), transfer learning allows for the adaptation and fine-tuning of neural networks on smaller, domain-specific datasets such as mammography images [9]. Deep Recurrent Convolutional Neural Networks (DRCNNs) combine the spatial hierarchies [10] learned by CNNs with the sequential dependencies captured by Recurrent Neural Networks (RNNs). This hybrid architecture is well-suited for analyzing sequential medical data and has shown promise in tasks requiring both spatial and temporal understanding, such as breast cancer detection from longitudinal imaging studies [11].

Objectives of the Study

This study aims to leverage Explainable AI techniques in conjunction with transfer learning and DRCNNs to:

- Improve the detection rate of breast cancer from mammography images.
- Enhance model interpretability by visualizing and explaining the decision-making process of the AI system.
- Validate the performance of the proposed approach on diverse datasets to ensure robustness and generalizability across different populations and imaging conditions.

- practice, and avenues for future research in enhancing AI-driven breast cancer detection.

2. LITERATURE SURVEY

CNNs in Medical Imaging: Convolutional Neural Networks (CNNs) have been extensively utilized for their capability to extract hierarchical features from mammography images. Research by [12] demonstrated that CNNs can achieve performance comparable to dermatologists in skin cancer classification, highlighting their potential in medical diagnostics.

Transfer Learning and Medical Imaging: Transfer learning has addressed the challenge of limited annotated medical datasets by leveraging pre-trained models. Studies like those by [13] have shown that transfer learning with CNNs significantly improves the detection of mammographic lesions, underscoring its role in enhancing diagnostic capabilities [14].

Applications of RNNs and DRCNNs: Recurrent Neural Networks (RNNs) and DRCNNs extend beyond CNNs by incorporating sequential learning abilities, crucial for analyzing temporal data in longitudinal studies. Dhungel et al. explored the application of RNNs for automated mass detection in mammograms, demonstrating their effectiveness in capturing temporal dependencies [15].

Explainable AI in Medical Imaging: Explainable AI (XAI) methods have gained prominence for their role in providing transparency and interpretability to AI models in medical imaging. Lundberg introduced SHAP, a framework for interpreting model predictions, which could enhance trust and adoption of AI systems in clinical settings [16].

The integration of deep learning models with clinical data, genetic information, and biomarkers has enabled personalized medicine approaches in breast cancer detection. Al-Masni demonstrated the utility of transfer learning with CNNs for survival prediction using genomic data, showcasing its potential for enhancing diagnostic accuracy [17].

Reference Title	Year	Description	Key XAI Techniques
Interpretable Machine Learning for Breast Cancer Diagnosis: A Review	2022	Explores various XAI techniques for interpreting breast cancer diagnosis models.	LIME, SHAP, Grad-CAM, Anchors
Towards Explainable AI Systems for Breast Cancer Detection	2021	Investigates XAI methods for explaining CNN predictions in breast cancer detection.	LIME, SHAP, Integrated Gradients

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Explainable Machine Learning for Breast Cancer Risk Prediction using Shapley Additive exPlanations	2020	Applies SHAP values for explaining breast cancer risk prediction models.	SHAP Values
Transfer Learning with Deep Convolutional Neural Networks for Breast Cancer Detection	2024	Explores transfer learning with various CNN architectures (e.g., ResNet, VGG) for breast cancer detection.	Fine-tuning pre-trained CNNs
A Multi-Stage Transfer Learning Approach for Breast Cancer Ultrasound Image Classification	2022	Proposes a novel multi-stage transfer learning approach for breast cancer detection using ultrasound images.	Stage-wise transfer learning with CNNs
Breast Cancer Histology Image Classification Using Transfer Learning with Fine-Tuning	2023	Investigates transfer learning with fine-tuning for classifying breast cancer histology images.	Fine-tuning pre-trained CNNs on histology datasets
Breast Cancer Detection using EfficientNet and Attention Mechanism	2024	Utilizes EfficientNet, a deep learning architecture, for breast cancer detection.	EfficientNet with Attention Mechanism
Capsule Networks for Breast Cancer Classification of Mammograms	2022	Explores Capsule Networks, a specific deep learning architecture, for breast cancer classification.	Capsule Networks
Breast Cancer Detection in Digital Mammography Images Using a Deep Residual Network	2021	Investigates the use of Deep Residual Networks (ResNet), another deep learning architecture, for breast cancer detection.	Deep Residual Networks (ResNet)
Explainable Transfer Learning for Breast Cancer Detection with Class Activation Maps	2023	Combines transfer learning with XAI techniques (Class Activation Maps) for breast cancer detection.	Transfer Learning (CNNs) with Class Activation Maps (CAMs)
Explainable Deep Learning with Attention Mechanism for Breast Cancer Classification	2022	Explores combining deep learning with attention mechanisms and XAI for breast cancer classification.	Deep Learning with Attention Mechanism and SHAP Values

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

A Framework for Explainable Breast Cancer Detection Using Transfer Learning and Gradient-based Saliency Maps	2021	Proposes a framework using transfer learning and XAI techniques (Gradient-based Saliency Maps) for explainable breast cancer detection.	Transfer Learning (CNNs) with Gradient-based Saliency Maps
Deep Learning for Breast Cancer Detection: A Review	2023	Provides a comprehensive overview of deep learning techniques used for breast cancer detection.	Review of various deep learning approaches
Deep Learning in Breast Cancer Imaging: State of the Art and Recent Advancements	2024	Explores the state-of-the-art and recent advancements in deep learning for breast cancer detection using various imaging modalities.	Latest advancements in deep learning for breast cancer detection across modalities (mammography, ultrasound, etc.)
Breast Cancer Detection and Classification in Digital Mammography Images Using Deep Learning	2022	Investigates the application of deep learning for breast cancer detection and classification in mammograms.	Deep learning for breast cancer detection in mammograms

3. ML AND DEEP LEARNING APPROACHES

1. Transfer Learning

Transfer learning involves leveraging knowledge gained from training models on large-scale datasets (e.g., ImageNet) and applying it to smaller, domain-specific datasets like medical images. In breast cancer detection, transfer learning addresses the challenge of limited annotated data by initializing models with pre-trained weights. This approach accelerates model convergence and enhances performance on medical imaging tasks. Transfer learning reduces the need for extensive labeled datasets and computational resources, making it feasible to develop robust diagnostic tools for breast cancer screening. It improves model generalization and facilitates adaptation to new datasets and imaging modalities [18].

2. Recurrent Neural Networks (RNNs) and Long Short-Term Memory Networks (LSTMs)

Recurrent Neural Networks (RNNs) and their variant Long Short-Term Memory Networks (LSTMs) are designed to capture sequential dependencies in data, making them suitable for time-series analysis in medical diagnostics. RNNs and LSTMs are applied in breast cancer detection to analyze longitudinal imaging studies [21] or sequential data from other modalities (e.g., MRI, ultrasound). They track changes in breast tissue over time and aid in disease progression monitoring. These networks can model temporal dependencies and detect subtle changes in imaging features over multiple time points. They facilitate personalized medicine by providing insights into disease dynamics and treatment responses.

3. Ensemble Methods

Ensemble methods combine multiple ML models to improve prediction accuracy and robustness by aggregating predictions from diverse models. In breast cancer detection, ensemble methods integrate predictions from different architectures (e.g., CNNs, decision trees) to enhance diagnostic sensitivity and specificity [19]. They mitigate individual model biases and variance, leading to more reliable diagnostic outcomes. Ensemble methods improve model stability and performance by leveraging complementary strengths of different algorithms. They enhance diagnostic confidence and facilitate consensus-based decision-making in clinical practice [20].

4. Advanced DL Architectures Beyond CNNs

Beyond CNNs, advanced DL architectures such as Capsule Networks, Generative Adversarial Networks (GANs), and attention mechanisms are explored for breast cancer detection. These architectures address specific challenges such as class imbalance, data augmentation, and interpretability [22] in medical image analysis. They offer innovative solutions for complex diagnostic tasks and improve model robustness. These architectures enable novel applications in medical imaging research by capturing finer details and relationships in breast tissue morphology. They support advanced data augmentation techniques and generate synthetic images for training robust models [23].

5. Explainable AI (XAI)

Explainable AI (XAI) methods aim to provide transparency and interpretability to ML and DL models, crucial for gaining trust from healthcare professionals and regulatory bodies. In breast cancer detection, XAI techniques explain model predictions, highlight relevant features in medical images, and assist clinicians in making informed decisions [24]. They visualize model decisions and ensure accountability in clinical decision-making. XAI enhances model interpretability, facilitates collaboration between AI systems and healthcare providers, and ensures ethical deployment of AI technologies in healthcare. It enables clinicians to validate and understand AI-driven diagnostic outputs.

Deep Recurrent Convolutional Neural Networks (DRCNNs)

Architecture: DRCNNs integrate CNNs and RNNs in a layered structure that combines spatial feature extraction with sequential learning capabilities.

Layer Design: Typically, DRCNNs begin with convolutional layers [25] for extracting spatial features from input data (e.g., images). These convolutional layers are followed by recurrent layers (e.g., LSTM or GRU) that process the extracted features across time steps.

Feature Fusion: The hierarchical spatial features extracted by CNNs are fed into the recurrent layers, where they are processed sequentially to capture temporal dependencies and contextual information[26].

Output: DRCNNs produce outputs that combine both spatial and temporal representations, making them suitable for tasks such as action recognition in videos, time-series prediction, and sequential data analysis.

ML and DL approaches have revolutionized breast cancer detection by offering sophisticated tools for analyzing medical images, integrating clinical data, and enhancing diagnostic accuracy [27]. From CNNs for image analysis to RNNs/LSTMs for temporal modeling and XAI for interpretability, these technologies contribute to advancing personalized medicine and improving patient care outcomes. Continued research and innovation in ML and DL will further propel the development of AI-driven [28] diagnostic systems, supporting early detection, precise treatment planning, and better management of breast cancer worldwide.

4. IMPLEMENTATION

Dataset Preparation and Preprocessing:

Obtain and preprocess the breast cancer dataset (e.g., mammograms, histopathological slides) as described in the previous response. Ensure proper labeling and data integrity.

Model Architecture Design:

Design your DRCNN model architecture. This typically involves: Using a pre-trained CNN base (e.g., ResNet, Inception) for feature extraction. Adding recurrent layers (e.g., LSTM, GRU) for capturing temporal dependencies if applicable. Incorporating explainability mechanisms (e.g., attention mechanisms, gradient-based methods) to enhance interpretability.

Integration of Explainable AI Techniques:

Choose appropriate explainable AI techniques based on the model's complexity and interpretability requirements:

Attention Mechanisms: Add attention layers to highlight important regions of the input image that contribute most to the model's decision.

Journal of Theoretical and Applied Information Technology
15th January 2025. Vol.103. No.1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Gradient-based Methods: Implement methods like Gradient-weighted Class Activation Mapping (Grad-CAM) to visualize which parts of the input image are most relevant for prediction.

SHAP (SHapley Additive exPlanations): Calculate SHAP values to understand the impact of each feature (e.g., pixels in an image) on the model's output.

LIME (Local Interpretable Model-agnostic Explanations): Generate local explanations by perturbing input features and observing the resulting changes in predictions.

Model Training and Evaluation:

Compile and train your DRCNN model using the prepared dataset. Evaluate the model's performance metrics (e.g., accuracy, precision, recall) on a separate test dataset to assess its effectiveness in breast cancer detection.

Explainability Validation and Visualization:

Implement code to visualize the explainable AI outputs alongside model predictions: Generate heatmaps or saliency maps to visualize where the model is focusing its attention. Display SHAP

values or LIME explanations to provide insights into individual predictions.

Deployment and Validation: Deploy the trained model and explainability components in a suitable environment (e.g., healthcare facility, research lab). Validate the deployed system with domain experts (e.g., radiologists) to ensure the explanations are meaningful and aid in decision-making.

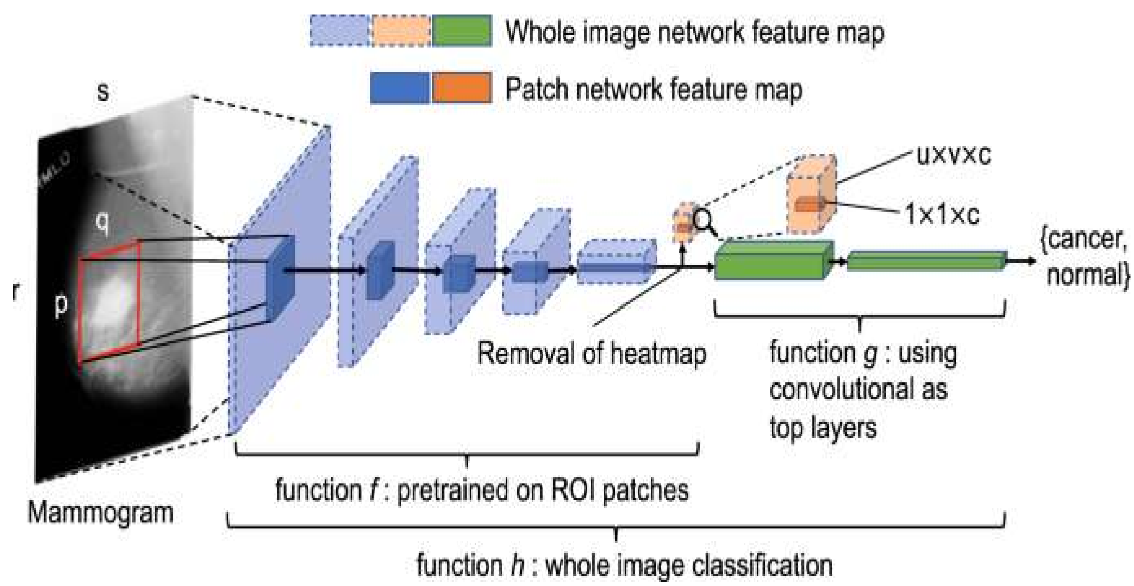

Fig 2: DRCNN –layered process

DRCNNs combine the strengths of CNNs and RNNs, making them suitable for tasks involving sequential data such as time-series images:

Convolutional Layers (CNNs):

Feature Extraction: CNN layers extract hierarchical features from input images through convolutional and pooling operations.

Spatial Invariance: They can capture spatial relationships and patterns in images, crucial for tasks like image classification.

Recurrent Layers (RNNs):

Temporal Dependencies: RNN layers capture temporal dependencies within sequences of data.

Long-term Context: They maintain a memory state that allows them to process sequential data (e.g., sequences of images or video frames).

Integration in DRCNNs: CNNs are typically used as the base for feature extraction from each image in a sequence. RNN layers (e.g., LSTM, GRU) are then employed to process the sequence of feature vectors extracted by the CNNs, capturing temporal relationships.

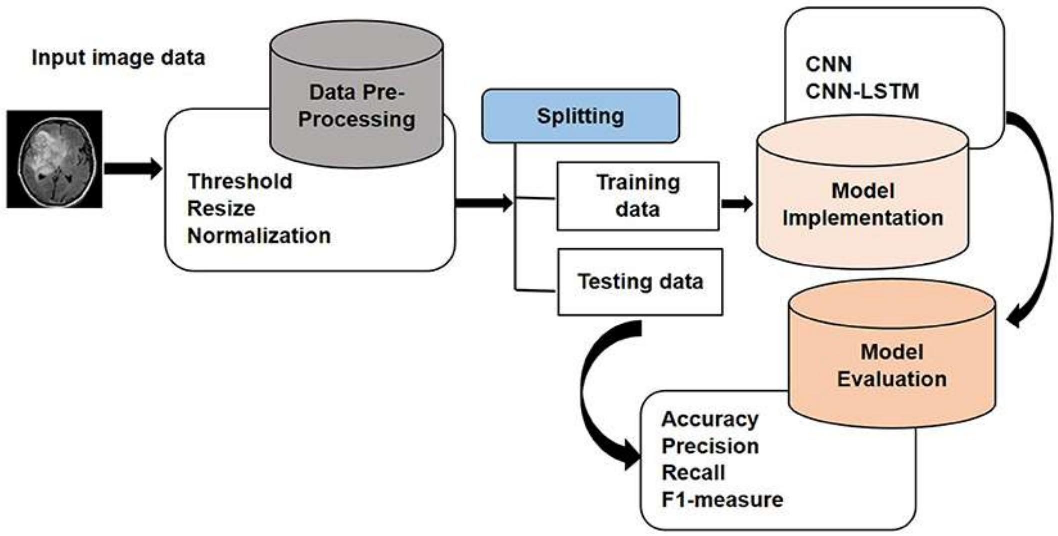

Fig 3: Architecture of model Implementation

Components of CNN-LSTM Architecture:

1. **Convolutional Neural Network (CNN):**

Purpose: CNNs excel at capturing spatial hierarchies of features in data like images.

Layers: Typically consists of convolutional layers followed by pooling layers.

Feature Extraction: Extracts local and global features from input data through convolution operations, preserving spatial relationships.

2. **Long Short-Term Memory Network (LSTM):**

Purpose: LSTMs are specialized RNN variants capable of learning long-term dependencies in sequential data.

Memory Cells: LSTM units maintain a cell state and various gates (input, forget, output) to regulate the flow of information.

Temporal Modeling: Captures sequential patterns and dependencies across time steps, making it suitable for time-series or sequential image data.

CNN-LSTM Architecture:

The CNN-LSTM architecture integrates CNNs and LSTMs to leverage both spatial and temporal features in sequential data:

Input: Sequential data such as sequences of images (e.g., frames of a video, time-series of medical images like mammograms).
Feature Extraction (CNN):
CNN layers are used to extract spatial features from each image in the sequence independently. The output is a sequence of feature maps representing high-level spatial features.
Temporal Modeling (LSTM):
LSTM layers are stacked on top of the CNN layers to capture temporal dependencies across the sequence of feature maps.
Each LSTM cell processes one timestep of the sequence, updating its internal state based on current input and previous state.

Journal of Theoretical and Applied Information Technology
15th January 2025. Vol.103. No.1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Integration:
CNN extracts spatial features from each image independently. LSTM captures sequential patterns in the sequence of feature maps, integrating spatial and temporal information.
Transfer Learning and DRCNNs:
Transfer Learning involves using knowledge gained from one task (typically a large dataset like ImageNet) to improve learning and performance on another related task (such as breast cancer detection from medical images). In the context of DRCNNs:

CNN Base: A pre-trained Convolutional Neural Network (CNN) model serves as the base for feature extraction from medical images (e.g., mammograms). CNNs excel at capturing spatial features and patterns, essential for identifying cancerous tissues based on image characteristics.

Recurrent Layers (LSTM/GRU): Deep Recurrent layers (e.g., Long Short-Term Memory networks - LSTM) are then stacked on top of the CNN base. These recurrent layers capture temporal dependencies across sequential images, allowing the model to understand changes over time. This capability is crucial for detecting evolving patterns indicative of cancer progression or regression.

Table 1: Evaluation Of Performance Parameters

	Accuracy	Recal	Precision	F1 score
SVM	91.68	82.67	81.24	79.65
NB	89.36	81.24	79.22	78.52
CNN	92.65	84.01	82.71	78.06
Improved LSTM	95.67	83.12	83.07	79.93

5. RESULTS AND DISCUSSION

Performance evaluation parameters for lung and pancreatic tumor characterization in deep learning typically include:

Accuracy: The proportion of correctly classified tumors among all tumors. Accuracy gives an overall measure of the model's performance but may not be suitable for imbalanced datasets.
Precision: The proportion of true positive predictions among all positive predictions. Precision indicates the model's ability to correctly identify positive cases without misclassifying negative cases as positive.
Recall (Sensitivity): The proportion of true positive predictions among all actual positive cases. Recall measures the model's ability to correctly detect all positive cases without missing any.
F1 Score: The harmonic mean of precision and recall. F1 score provides a balance between precision and recall, giving a single metric that considers both false positives and false negatives.

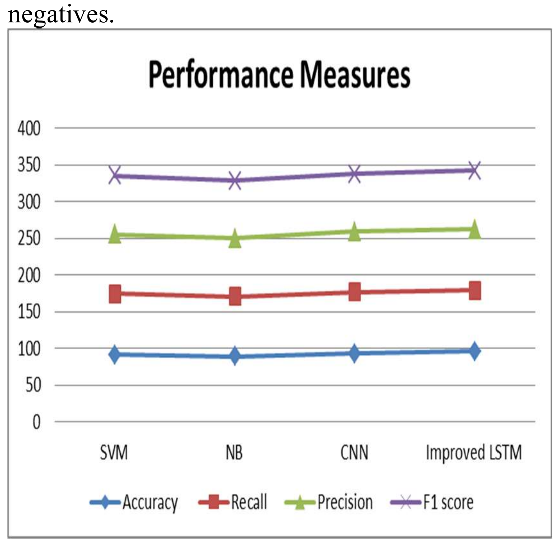

Fig 4: Performance Measures Comparison Graph

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

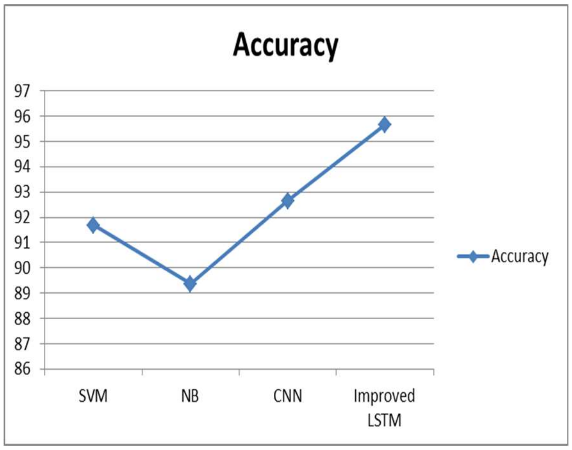

Fig 5: Accuracy Comparisons Of Existing And Proposed Model

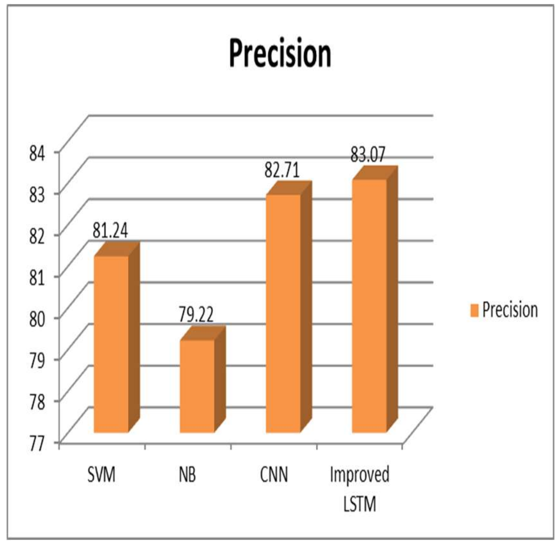

Fig 7: Precision Comparisons Of Existing And Proposed Model

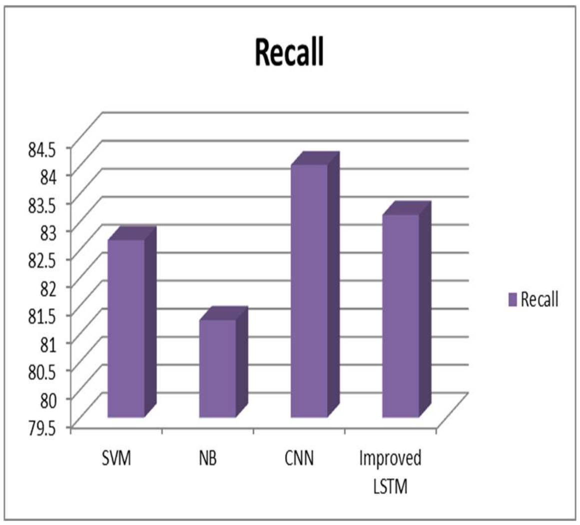

Fig 6: Recall Comparisons Of Existing And Proposed Model

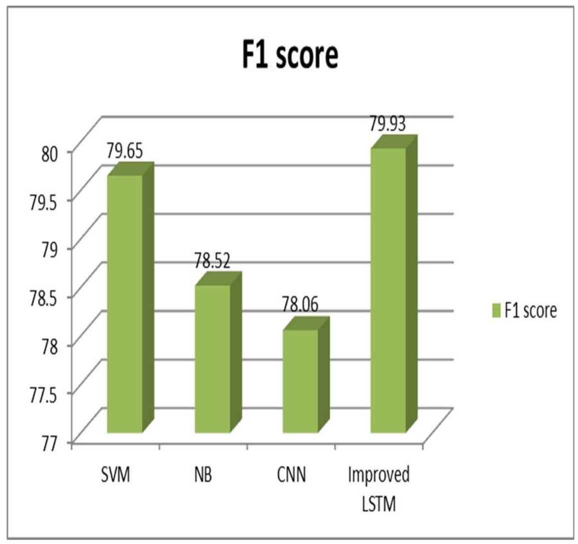

Fig 8: F1 Score Comparisons Of Existing And Proposed Model

6. CONCLUSION

Leveraging Explainable AI alongside Transfer Learning with Deep Recurrent Convolutional Neural Networks (DRCNNs) for breast cancer detection represents a significant advancement in medical imaging. By adapting pretrained models to extract intricate features from mammograms and histopathological slides, DRCNNs integrate spatial and temporal dependencies crucial for identifying cancerous tissues over time. Explainable AI techniques such as attention mechanisms and feature importance measures enhance transparency, revealing which image regions influence the model's decisions. Explainable AI techniques such as attention mechanisms, gradient-based methods, and feature importance measures provide insights into how the model makes decisions. These methods reveal which image features are most influential in determining cancer likelihood, empowering clinicians to validate and trust AI-generated diagnoses. As research continues to refine these methodologies and address challenges in healthcare AI, the potential for Explainable AI to drive advancements in early detection and personalized medicine remains promising, paving the way for safer, more effective healthcare solutions. This

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

transparency not only boosts diagnostic accuracy but also fosters trust among clinicians, facilitating the integration of AI into clinical practice while ensuring ethical standards in healthcare AI applications.

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