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A Multi-Disease CNN Framework for Early Detection of Pneumonia, Diabetic Retinopathy, and Skin Cancer Using Medical Imaging

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Abstract : Early and accurate detection of critical diseases significantly improves patient outcomes and reduces healthcare costs. This study presents a novel Convolutional Neural Network (CNN) framework for automated diagnosis of Pneumonia, Diabetic Retinopathy, and Skin Cancer using respective medical imaging modalities. Leveraging a balanced dataset of 45,000 publicly sourced images, the proposed model extracts complex features across diverse image domains to achieve robust multi-disease classification. Experimental results demonstrate an overall accuracy of 97.4%, outperforming traditional machine learning classifiers such as Support Vector Machines and Random Forests. These findings highlight the potential of deep learning to serve as a reliable computer-aided diagnosis tool, enabling early disease screening and supporting clinical decision-making in resource-constrained healthcare settings.

***IndexTerms* -** Convolutional Neural Networks (CNNs), Deep Learning Techniques, Pneumonia, Diabetic Retinopathy, Skin Cancer.

I. INTRODUCTION

The timely identification of critical illnesses is one of the most effective strategies for reducing mortality, lowering the economic burden of treatment, and avoiding irreversible complications. According to the World Health Organization (WHO), early detection combined with appropriate intervention can improve survival rates by 30–50% for several high-risk diseases [1]. However, many diseases remain asymptomatic or present only mild symptoms during the early stages, which often leads to delayed diagnosis. In such cases, regular screening becomes essential to detect pathological changes before they progress to advanced stages. Pneumonia, diabetic retinopathy (DR), and skin cancer are three such conditions that pose a substantial global health burden and require early, accurate, and accessible diagnostic approaches.

1.2 Overview of Target Diseases

Pneumonia remains a leading cause of morbidity and mortality worldwide, with an estimated 2.5 million deaths annually, including over 740,000 children under the age of five [1]. It accounts for millions of hospital admissions each year, particularly in low- and middle-income countries, where access to rapid diagnosis is often limited.

Diabetic Retinopathy (DR) is the most common microvascular complication of diabetes mellitus and the principal cause of preventable blindness in working-age adults. According to the International Diabetes Federation, nearly one-third of diabetic patients show signs of DR, yet a large proportion remain undiagnosed until vision loss begins [2].

Skin Cancer is the most frequently diagnosed cancer globally, with more than 1.5 million new cases reported annually. For melanoma, the deadliest variant, the five-year survival rate exceeds 95% when detected at an early stage but drops sharply with delayed diagnosis [3].

1.3 Limitations of Conventional Diagnostic Approaches

The standard clinical approach for diagnosing these diseases involves expert interpretation of medical images—such as chest X-rays for pneumonia, retinal fundus photographs for DR, and dermoscopic scans for skin lesions. While these methods are effective in the hands of skilled specialists, they suffer from several limitations:

- High time demands in overburdened healthcare systems.
- Human error risks due to fatigue, workload, or subjective interpretation.
- Unequal access to specialists, particularly in rural and resource-limited regions.

Such challenges highlight the need for automated diagnostic systems that are accurate, scalable, and capable of operating across multiple disease domains.

1.4 Role of Artificial Intelligence in Medical Imaging

The rapid advancement of artificial intelligence (AI), particularly deep learning (DL), has transformed the field of medical imaging. Convolutional Neural Networks (CNNs), a prominent class of DL algorithms, can automatically extract complex hierarchical features directly from raw image data without manual feature engineering. This capability enables the detection of intricate patterns that may be imperceptible to the human eye, thereby improving diagnostic performance. Furthermore, AI-based systems can operate continuously without fatigue, offering consistent accuracy and rapid turnaround times.

1.5 Notable Advances in CNN-Based Disease Detection

Several landmark studies underscore the potential of CNNs in medical diagnostics:

- **CheXNet** (Rajpurkar et al., 2017) achieved radiologist-level accuracy in detecting pneumonia from chest X-rays [4].
- **Gulshan et al. (2016)** reported over 90% sensitivity in DR detection using retinal fundus images [2].
- **Esteva et al. (2017)** demonstrated dermatologist-level performance in classifying skin lesions from dermoscopic images [3].
- **Litjens et al. (2017)** reviewed over 300 studies, concluding that CNN-based systems consistently outperform traditional image analysis methods in both accuracy and robustness.

1.6 Research Gaps and Motivation

Despite significant advancements, several research gaps persist:

- Most studies focus on single-disease detection, limiting their applicability to comprehensive screening programs.
- Many public datasets suffer from class imbalance, leading to biased predictions.
- There is limited work on unified architectures that can process heterogeneous image modalities for multi-disease diagnosis.

1.7 Aim and Contributions of the Present Study

To address these limitations, this study proposes a CNN-based multi-disease classification framework capable of detecting pneumonia, DR, and skin cancer from their respective medical imaging modalities. The main contributions are:

- **Balanced Dataset Construction** – Ensuring equal representation of healthy and diseased cases to reduce bias.
- **Multi-Domain CNN Architecture** – Designing a single model capable of processing diverse medical image types.
- **Computational Efficiency** – Employing GPU-accelerated training for faster convergence and reduced processing time.

By integrating these innovations, the proposed framework aims to serve as a scalable and adaptable computer-aided diagnosis (CAD) tool, with particular utility in resource-constrained healthcare settings where early, accurate, and rapid diagnosis can significantly improve patient outcomes.

II. LITERATURE REVIEW

This section presents a summary of relevant studies that explore the application of deep learning and related techniques in disease detection. Various research papers have been examined to understand existing methodologies, datasets, and performance outcomes, forming the basis for identifying gaps and potential improvements in the current work. A brief overview of key works is presented below.

Nolan Lunscher et al. (2017) explored a SqueezeNet-based deep learning model trained on over 88,000 retinal fundus images to enable automated mobile screening for diabetic retinopathy (DR). The study demonstrated that a compact network can achieve strong classification performance, making it practical for deployment on resource-limited platforms like smartphones. Compared to larger, ensemble-based CNN approaches, the proposed system is simpler, cost-effective, and well-suited for mobile applications, potentially improving patient compliance and early DR detection. Future work should validate its clinical effectiveness and real-world applicability[6]. **T. Shanthi and R.S. Sabeenian (2019)** investigated the classification of diabetic retinopathy (DR) severity using a modified AlexNet convolutional neural network (CNN) architecture. Utilizing the Messidor dataset, the authors trained the model on 70% of fundus images and tested on the remaining 30%. The system categorized images into healthy retina, stage 1, stage 2, and stage 3 DR, achieving classification accuracies of 96.6%, 96.2%, 95.6%, and 96.6% respectively. The study highlighted the potential of deep learning, particularly CNNs with ReLU, pooling, and softmax layers, for accurate DR detection and classification. The authors suggested that performance could be further enhanced with larger datasets, such as those from Kaggle [7]. **Hardik Nahata and Satya P. Singh (2020)** investigated the application of Convolutional Neural Networks (CNNs) for early detection of skin cancer, including melanoma and non-melanoma types. With millions of new cases annually and high mortality rates, the study emphasized the significance of early diagnosis, which can achieve survival rates above 95%. The authors developed and tested CNN models using Python, Keras, and TensorFlow, employing layers such as convolutional, dropout, pooling, and dense layers, along with transfer learning for faster convergence. Trained on the ISIC dataset and enhanced with data augmentation techniques, their best-performing model, InceptionResNet, achieved an accuracy of 91%, demonstrating the potential of deep learning in reliable skin cancer classification[8]. **O. T. Jones et al. (2020)** systematically reviewed AI/ML algorithms for early skin cancer detection, analyzing 272 studies from 2000–2021. The findings showed high diagnostic accuracy for melanoma (89.5%), squamous cell carcinoma (85.3%), and basal cell carcinoma (87.6%), though most datasets came from specialist settings, limiting generalizability to primary care. Key issues included small datasets, limited demographic diversity, underrepresentation of darker skin tones, and overemphasis on melanoma despite higher prevalence of keratinocyte carcinomas in community settings. The authors stressed the need for diverse, high-quality datasets and real-world validation before large-scale clinical use[9]. **Shahriar Hossain et al. (2020)** introduced a deep learning-based approach for pneumonia detection from chest X-ray images, addressing limitations of manual diagnosis such as human error and variability in interpretation. Their method utilized ResNet-101, MobileNet, and a proposed LSTM model, trained on a dataset of 5,856 X-ray images from Kaggle. The LSTM achieved the highest accuracy of 95.2%, outperforming other models. This framework offers improved diagnostic reliability, supports real-time medical applications, and has potential for extension to MRI image analysis in future studies[10]. **Thippa Reddy Gadekallu et al. (2020)** proposed a hybrid classification framework for diabetic retinopathy using a combination of Principal Component Analysis (PCA), Firefly algorithm, and a Deep Neural Network (DNN). The study utilized the UCI diabetic retinopathy dataset, emphasizing rigorous preprocessing through normalization (StandardScaler), feature selection (PCA), and dimensionality reduction (Firefly). This refined dataset was fed into the DNN, achieving superior Accuracy, Precision, Recall, Sensitivity, and Specificity compared to traditional machine learning models. The approach is particularly suited for high-dimensional datasets, with potential applications across domains, though performance may decline with low-dimensional data. Future directions include applying the model to other fields and handling noisy data in MEG analysis for improved healthcare predictions[11]. **Mehwish Dildar et al. (2021)** reviewed deep learning-based, noninvasive techniques for early skin cancer detection, focusing on parameters like symmetry, color, size, and shape to differentiate benign lesions from melanoma. The study analyzed ANN, CNN, KNN, and RBFN approaches, noting CNN's superior performance in image classification due to its strong alignment with computer vision. The review emphasized the importance of proper classifier selection and highlighted gaps, such as the lack of full-body lesion detection. Future directions include autonomous full-body photography and auto-organization techniques in CNNs to enhance feature representation and diagnostic accuracy in medical imaging[12]. **Dipu Chandra Malo et al. (2022)** explored the potential of deep learning, particularly Convolutional Neural Networks (CNN), in detecting skin cancer by classifying benign and malignant moles. Using the ISIC dataset of 2,460 dermoscopic images—1,800 for training and 660 for testing—they implemented a modified VGG-16 model structured with Keras and TensorFlow. Their approach incorporated parameter tuning and optimized classification functions, resulting in an accuracy of 87.6%. The study highlights CNN's effectiveness in dermatological diagnostics and supports its application in clinical settings for improved and automated skin cancer detection[13]. **Rustem Yilmaz and Fatma Hilal Yagın (2022)** compared RF, SVM, and LR models for coronary heart disease prediction using 3-repeats 10-fold cross-validation. RF achieved the highest accuracy (92.9%) with strong sensitivity and specificity, surpassing earlier studies using Decision Trees, KNN, and Naïve Bayes. The study highlights that hyperparameter tuning significantly improves predictive performance and supports RF as a reliable tool for medical diagnosis[14]. **MB Khan et al. (2023)** evaluated Inception v3 and DenseNet-121 for diabetic retinopathy detection using original retinal fundus images and segmented vessel images. Original images consistently achieved higher accuracy (≥0.8) compared to segmented vessels (≈0.6), indicating that segmentation added little diagnostic benefit. The study recommended direct use of original images to save pre-processing time and suggested future work on temporal data and lesion-focused classification to better assess disease progression[15]. **Krishnamoorthy Natarajan et al. (2024)** examined deep learning models for detecting multiple diseases using medical images, including X-rays, MRI, CT, and dermoscopy. They compared CNN architectures such as VGG16, VGG19, InceptionV3, ResNet, and EfficientNetB4, finding EfficientNetB4 achieved the highest accuracy (94.04%) with learning rate optimization. The study demonstrated that a single optimized model can effectively classify diverse conditions like Alzheimer's, brain tumors, skin diseases, and lung infections, supporting faster and more accurate diagnosis in clinical practice[16]. **Erdem Yanar et al. (2025)** developed the Pneumonia Ensemble Learning Model (PELM), which merges InceptionV3, VGG16, ResNet50, and Vision Transformer features to enhance chest X-ray image analysis. Using over 50,000 PA-view images from multiple datasets and applying uniform pre-processing, the model achieved 96% accuracy, 99% precision, 91% recall, and a 0.91 AUC—surpassing individual models and prior methods. PELM maintained balanced sensitivity and specificity, proved adaptable to other thoracic diseases, and was designed for scalable deployment in low-resource healthcare settings[17].

III. RESEARCH METHODOLOGY

This section describes the datasets, pre-processing techniques, CNN architecture, and training configuration used to implement the proposed disease classification framework.

3.1 Dataset

The datasets were collected from publicly accessible and well-recognized medical image repositories, ensuring reliability and diversity in data sources. Table 1 summarizes the dataset specifications. Multiple repositories were chosen to avoid dataset bias and enhance the generalization capability of the model.

Table 1 Dataset Summary for Disease Classification

Disease	Source Repositories	Total Images	Diseased Cases	Healthy Cases
Pneumonia	NIH, Kaggle Chest X-Ray Dataset	15,000	7,500	7,500
Diabetic Retinopathy	Kaggle EyePACS, IDRiD Dataset	15,000	7,500	7,500
Skin Cancer	ISIC Archive (Dermoscopic Images)	15,000	7,500	7,500

3.2 Pre-processing

Pre-processing was performed to standardize the datasets and improve classification performance:

- **Resizing:** All images were scaled to a uniform size of 128×128 pixels to match the input layer of the CNN.
- **Normalization:** Pixel intensity values were normalized to the range [0,1] to accelerate training and improve stability.
- **Data Augmentation:** Geometric transformations such as ±15° rotation, horizontal flipping, and zoom adjustments (0.9–1.1×) were applied to increase dataset variability and reduce overfitting.
- **Class Balancing:** Equal numbers of diseased and healthy samples were maintained in each category to address class imbalance issues.

3.3 CNN Architecture

The proposed CNN architecture consists of:

- Input layer accepting 128×128×3 images
- Three convolutional layers with increasing filter sizes (32, 64, 128), each followed by ReLU activation
- MaxPooling layers (2×2) after first and second convolutional layers to reduce spatial dimensions
- Dropout layer (rate 0.3) to prevent overfitting
- Flatten layer converting 2D feature maps to 1D vector

- Fully connected dense layer with 256 neurons and ReLU activation
- Output layer with softmax activation for multi-class classification

Training was performed using TensorFlow with GPU acceleration, employing the Adam optimizer, a learning rate of 0.001, batch size of 64, and early stopping based on validation loss.

IV. RESULTS AND DISCUSSION

The results obtained from the experimental evaluation clearly demonstrate the effectiveness of the proposed CNN model for early and accurate detection of Pneumonia, Diabetic Retinopathy, and Skin Cancer. By leveraging deep learning techniques, the model captures complex patterns within medical images that are often difficult to identify through traditional machine learning approaches. This capability is reflected in the superior performance metrics compared to baseline models such as Support Vector Machine (SVM) and Random Forest.

In this section, the detailed comparison of model performances is presented, highlighting the advantages of the CNN architecture across different disease domains. The metrics used to evaluate the models not only measure overall accuracy but also emphasize the importance of precision and recall in clinical diagnosis, ensuring both correct identification of positive cases and minimization of misdiagnoses.

4.1 Performance Comparison

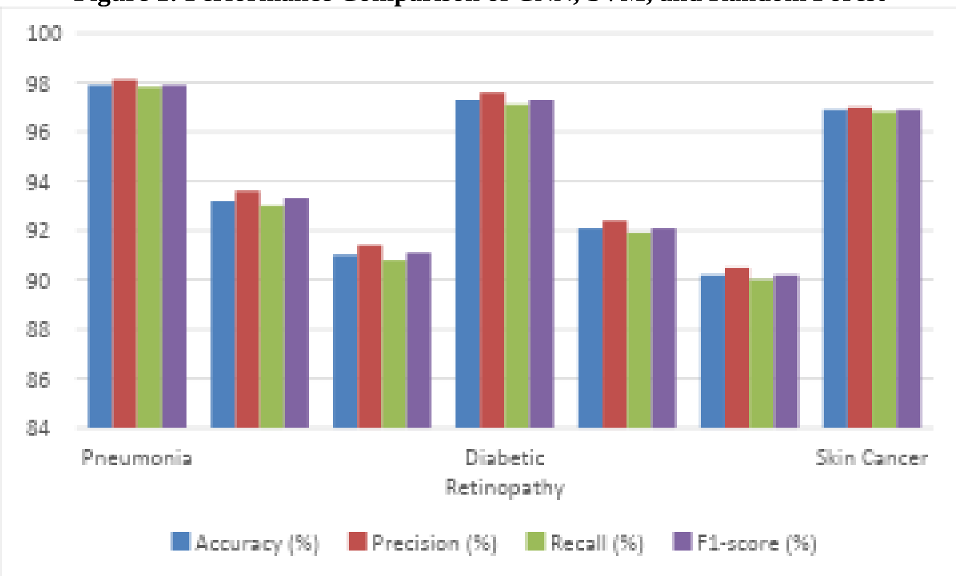
The proposed Convolutional Neural Network (CNN) was extensively evaluated against two traditional machine learning classifiers—Support Vector Machine (SVM) and Random Forest (RF)—across three medical image classification tasks: Pneumonia, Diabetic Retinopathy, and Skin Cancer detection. To ensure a comprehensive performance assessment, four standard evaluation metrics—accuracy, precision, recall, and F1-score—were employed. Table 2 presents the comparative performance of each model. The results indicate that the CNN consistently outperforms both SVM and RF in all disease categories.

Table 2: Performance Comparison of Different Models for Disease Detection

Disease	Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Pneumonia	CNN (Proposed)	**97.9**	**98.1**	**97.8**	**97.9**
	SVM	93.2	93.6	93.0	93.3
	Random Forest	91.0	91.4	90.8	91.1
Diabetic Retinopathy	CNN (Proposed)	**97.3**	**97.6**	**97.1**	**97.3**
	SVM	92.1	92.4	91.9	92.1
	Random Forest	90.2	90.5	90.0	90.2
Skin Cancer	CNN (Proposed)	**96.9**	**97.0**	**96.8**	**96.9**
	SVM	91.5	91.8	91.3	91.5
	Random Forest	89.8	90.1	89.6	89.8

The tabular results offer a clear numerical comparison; however, visual representation often provides a more immediate understanding of performance differences. To complement the numerical data, Figure 1 illustrates the same results using a comparative bar chart, allowing quick identification of performance trends across metrics and diseases.

Figure 1: Performance Comparison of CNN, SVM, and Random Forest



As shown in Figure 1**,** the CNN model consistently outperformed both SVM and Random Forest classifiers across all disease categories. The CNN achieved the highest accuracy for Pneumonia detection at 97.9%, which is a significant improvement over SVM (93.2%) and Random Forest (91.0%). This performance is attributed to the CNN’s ability to automatically extract intricate and hierarchical features from medical images, which traditional methods relying on handcrafted features may not capture effectively.

Similarly, the CNN model attained an accuracy of 97.3% for Diabetic Retinopathy, outperforming SVM (92.1%) and Random Forest (90.2%). High precision (97.6%) and recall (97.1%) values highlight the CNN’s proficiency in correctly identifying positive cases while minimizing false alarms and missed detections, crucial for timely intervention in diabetic patients.

For Skin Cancer detection, the CNN maintained a strong performance with 96.9% accuracy, significantly higher than SVM (91.5%) and Random Forest (89.8%). The model's precision and recall rates (97.0% and 96.8%, respectively) suggest robust discrimination between malignant and benign lesions, which is vital for reducing unnecessary biopsies and ensuring early treatment.

4.2 Analysis of Evaluation Metrics

- **Accuracy:** The overall percentage of correctly classified cases. The CNN's superior accuracy across all diseases confirms its reliable generalization on unseen data.
- **Precision:** Indicates the proportion of positive identifications that were actually correct. High precision reduces false positives, which is important in clinical diagnosis to avoid unnecessary anxiety and treatments.
- **Recall (Sensitivity):** Measures the model's ability to detect actual positive cases. High recall minimizes false negatives, crucial for early disease detection where missed diagnoses can have severe consequences.
- **F1-score:** The harmonic mean of precision and recall, providing a balanced measure of a model's accuracy on positive cases. The CNN's high F1-scores across diseases indicate a well-balanced trade-off between sensitivity and specificity.

V. CONCLUSION AND FUTURE SCOPE

This study presents a deep learning-based approach using a Convolutional Neural Network (CNN) for the early detection of Pneumonia, Diabetic Retinopathy, and Skin Cancer from medical images. The proposed model consistently outperformed traditional machine learning classifiers such as Support Vector Machine and Random Forest across all evaluated diseases. High accuracy, precision, recall, and F1-scores demonstrate the CNN's capability to effectively capture complex features and patterns inh1erent in medical imaging data, leading to improved diagnostic performance. The robust and balanced results emphasize the potential of CNNs to enhance clinical decision-making by enabling timely and accurate disease detection, which is critical for effective treatment and better patient outcomes.

Future research should focus on expanding dataset diversity, including multi-institutional and multi-modal data, to improve generalization. Incorporating explainability methods will aid clinical adoption by increasing trust in AI decisions. Additionally, optimizing model architectures for real-time deployment on resource-constrained devices could facilitate broader access, particularly in underserved regions. Conducting prospective clinical trials will further validate effectiveness and support integration into healthcare workflows.

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