

Multi Disease Prediction using Deep Learning

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I. ABSTRACT

Early and efficient diagnosis of diseases has proven to be crucial for enhancing the efficacy of treatment of the same. The development of advanced technologies such as artificial intelligence, more specifically deep learning, has enabled automated analysis of medical images with greater efficiency. The current paper suggests the implementation of a hybrid deep learning system referred to as Multi Disease Prediction using Deep Learning (MDPDL) for identification of diseases from medical images that include brain tumors, lungs infections, bone fractures, skin diseases, and diseases related to the eyes. The proposed method involves the use of CNN for feature extraction, GA for optimizing those features, Bi-LSTM for classification purposes, and Attention mechanism to focus on important pathological regions. Comparison has been made between the proposed deep learning model and traditional machine learning classifiers such as KNN, Naive Bayes, and SVM. Model accuracy is about 96%.

Keywords: Multi-Disease Prediction, Deep Learning, CNN, Bi-LSTM, Genetic Algorithm, Attention Mechanism, Medical Image Classification.

II. INTRODUCTION

Medical imaging is an indispensable part of the modern health care system, which helps to detect, diagnose, and monitor a variety of conditions that affect various organ systems. Various imaging techniques include MRI, CT scans, X-rays, dermoscopic imaging, retinal fundus imaging

offer precise structural details that facilitate the detection of anomalies. Nonetheless, the manual analysis of medical imagery necessitates a significant level of knowledge and understanding of the domain, takes much time, and may vary from one person to another. In emergency situations, late detection may have serious consequences on patients' health.

The increase in the amount of imagery in hospitals and clinics has led to the demand for intelligent

classification algorithms. Conventional machine learning classifiers like K-Nearest Neighbor (KNN), Naive Bayes (NB), Decision Tree, and Support Vector Machine (SVM) have been employed for classifying diseases. While these models achieve reasonable accuracy, their performance is dependent on manually designed features. Feature engineering is knowledge-intensive and can be incapable of discovering intricate patterns that exist within medical imaging data. In addition

However, CNNs have some drawbacks. The high-dimensional nature of the representation contains many redundancies and noise, leading to inefficient computation. In addition, a fully convolutional approach fails to provide sufficient context about the sequential relationship of the extracted features. This could be problematic for cases involving multiple disease classifications, which differ in each organ's pathologies.

To solve these problems, hybrid deep learning models have been developed. By combining optimization methods with deep learning, the features' relevance becomes more pronounced.

The Genetic Algorithm and other evolutionary algorithms are highly suited for feature selection because they emulate the natural selection process to find optimal sets of features that optimize accuracy and reduce redundancy in order to enhance efficiency and improve the generalization capability of the models.

Additionally, recurrent neural networks (RNNs),

In particular, the Long Short-Term Memory (LSTM) network can learn long-term dependencies in sequence-based datasets. The Bidirectional LSTM (Bi-LSTM) algorithm further extends this functionality by analyzing input features in both forward and reverse directions, thereby understanding all possible contextual relations. Applying Bi-LSTM to extract clinical pathological features from medical images using CNN increases the model's ability to classify the data more effectively.

The attention layer has also been a significant development in deep learning. The attention layer helps assign greater weightage to the region of interest in the image and minimizes the background noise. This ensures that the predictions are based on relevant regions of the image in medical diagnostic applications.

Whereas many studies have concentrated on developing systems that are capable of recognizing specific diseases, very few studies have attempted to build architectures that diagnose multiple diseases in various body systems simultaneously.

Most of the models developed thus far have been tailored towards identifying only a particular pathology, which limits the potential applicability of these models to actual healthcare practices. Traditional machine learning algorithms such as K-Nearest Neighbor (KNN), Naive Bayes (NB), Decision Tree, and Support Vector Machine (SVM) have been used for classifying medical conditions.

III. RELATED WORK

Litjens et al. (2017) provided an overview of deep learning techniques in medical image analysis, focusing on CNN-based approaches to detection, segmentation, and classification, while pointing out difficulties such as data paucity and model generalization [1]. Rajpurkar et al. (2017) created the CheXNet, a deep CNN system that can detect pneumonia at radiologist-level accuracy based on chest X-ray images, with high accuracy on large datasets containing labeled medical images [2]. Esteva et al. (2017) constructed a deep neural network that performs skin cancer classification with dermatologist-level accuracy from dermoscopic images and large labeled datasets [3]. Gulshan et al. (2016) developed a deep learning-based system for detecting diabetic retinopathy in retinal images, with high sensitivity and specificity compared to expert ophthalmologists [4]. Wang et al. (2017) constructed ChestX-ray14, a large database with 14 disease labels, allowing benchmarking and research of multi-label classification models on chest X-ray images [5]. Codella et al. (2019) published the ISIC

Challenge Dataset: ISIC provides the ISIC archive, which includes an advanced challenge dataset to promote automated skin lesion analysis and melanoma detection through deep learning based classification and segmentation methods [6]. Musculoskeletal Radiograph Dataset: The MURA dataset is designed by Rajpurkar et al. in 2017 for musculoskeletal radiograph analysis that helps to detect abnormalities through deep learning based models with performance comparable to radiologists [7]. Chest X-Ray Dataset: The VinDr-CXR dataset was proposed in 2022 to facilitate the development of robust medical imaging model through an extensively annotated chest X-ray dataset with annotations from expert radiologists [8]. Biomedical Image Segmentation: Ronneberger et al. have provided an architecture named U-Net for biomedical image segmentation to provide accurate localization using an encoder-decoder architecture [9].

S.No	Title	Problem Statement	Methodology used	Limitations
1	Deep Learning in Medical Image Analysis.	Lack of structured overview of deep learning applications in medical imaging.	Survey of CNN-based techniques for classification, detection, segmentation.	Limited to review; no experimental validation; rapidly evolving field.
2	CheXNet: Pneumonia Detection.	Accurate pneumonia detection from chest X-rays.	DenseNet-based deep CNN trained on ChestX-ray14 dataset.	Dataset bias; limited disease scope; requires large labeled data.

3	Skin Cancer Classification.	Need for accurate automated skin cancer diagnosis.	Deep CNN trained on large dermoscopic image dataset.	Requires high-quality images; generalization issues across populations.
4	Diabetic Retinopathy Detection.	Early detection of diabetic retinopathy from retinal images.	Deep learning model (CNN) with large annotated dataset.	High computational cost; dependency on image quality.
5	ChestX-ray14 Dataset.	Lack of large-scale labeled chest X-ray datasets.	Creation of dataset with 14 disease labels; benchmarking models.	Label noise; weak annotations; limited clinical validation.
6	ISIC 2018 Challenge.	Need for standard dataset for skin lesion analysis.	Dataset + challenge for segmentation and classification tasks.	Class imbalance; variability in lesion appearance.
7	MURA Dataset.	Automated abnormality detection in musculoskeletal radiographs.	Large dataset + deep CNN models for classification.	Limited anatomical diversity; annotation subjectivity.
8	VinDr-CXR Dataset.	Need for high-quality annotated chest X-ray dataset.	Expert-labeled dataset with bounding boxes for abnormalities.	Limited geographic diversity; annotation cost.
9	U-Net Architecture.	Accurate biomedical image segmentation with limited data.	Encoder-decoder CNN with skip connections.	Requires tuning; may overfit small datasets.

10	DenseNet Architecture.	Improve feature reuse and reduce parameters in CNNs.	Dense connectivity between layers in CNN architecture.	Memory intensive; complex implementation.
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IV. METHODOLOGY

The suggested MDPDL framework operates on a hybrid approach that combines deep learning and evolutionary optimization methods to facilitate accurate classification of multiple diseases across various organs. The framework aims to provide a structured way of processing medical images, extracting relevant representations, optimizing the selection of features, and conducting contextual classification.

First, labeled image data related to various disease classes—such as diseases affecting the brain, lungs, bones, skin, and eyes—are gathered and curated into training sets. Image pre-processing procedures such as resizing, normalization, and augmentation are implemented to standardize the size of images and enhance the generalization ability of the model. CNN models are then utilized for automatic extraction of spatial features within the pre-processed images.

CNN models learn discriminative features such as edges, textures, structural abnormalities, and lesions directly from images through their layers..

Nevertheless, deep representations of features by using CNNs might include unnecessary or irrelevant data.

Thus, in order to overcome such a problem, an optimization component based on Genetic Algorithm (GA) is proposed to perform feature selection. In this regard, GA repeatedly assesses feature subsets using a fitness function, which is computed according to classification performance. Using selection, crossover, and mutation mechanisms, GA ultimately finds an optimal feature subset that yields the highest accuracy rate while keeping low computational load.

The selected feature subset is utilized for classification by employing a Bidirectional Long Short-Term Memory (Bi-LSTM) architecture. Unlike feedforward models, the bidirectional nature of Bi-LSTM allows it to analyze feature sets from both directions and learn its context more effectively. Consequently, such a process enables to detect specific diseases irrespective of medical imaging type used. Finally, to enhance prediction performance, attention can be added to the architecture.

The attention mechanism allocates dynamic weights to the appropriate feature representations so that the model concentrates on disease-specific regions and neglects background features. It increases transparency and helps improve accuracy in diagnosis. Finally, the trained hybrid model is evaluated based on

Performance measures include accuracy, precision, recall, and F1-score. The performance is further confirmed by comparing the proposed classifier with conventional machine learning classifiers.

In general, the methodology involves spatial features, evolutionary computing, context-aware modeling, and attention modeling in one comprehensive framework for multiple disease prediction.

V. SYSTEM ARCHITECTURE



This suggested Multi-Disease Prediction Using Deep Learning (MDPDL) framework will function as a scalable, modular, and hybrid approach for making diagnosis of diseases by using both deep learning and evolutionary methods. The architecture of MDPDL is designed to facilitate medical imaging data processing to predict different diseases from different organs effectively. This proposed Multi Disease Prediction using Deep Learning (MDPDL) approach will work as a hybrid, modular, and scalable architecture that employs both deep learning and evolutionary methods to develop a high-accuracy image classifier for diseases in medical images. The MDPDL architecture works as a sequential processing pipeline in which

module plays a distinct role within the entire process of diagnosis.

The first layer consists of a systematic data acquisition process where medical images are collected from various diagnostic fields like brain MRI scans, chest X-rays, bone scans, dermoscopic skin scans, and retinal fundus scans. These images could differ in resolution, lighting, and contrast. In order to prepare the data for training the model, there is a need for a preprocess step where all the collected data goes through. The main tasks of the preprocess step include changing resolution, normalizing pixel values to ensure stability, eliminating noise artifacts, and adding additional data using techniques like rotation, flipping, and scaling.

VI. WORKFLOW

The workflow of the Multi Disease Prediction using Deep Learning (MDPDL) approach involves a well-organized and systematic process that guarantees effective data management, optimal feature extraction, and accurate disease diagnosis.

The first stage of the process involves dataset collection, which entails collecting labeled images of various diseases. The next phase is the pre-processing phase, which includes resizing, normalization, noise removal, and data augmentation techniques to increase consistency in the dataset and improve the performance of the model.

Following the pre-processing stage, the images are fed into the

Module for spatial hierarchy convolutional neural network (CNN). It extracts low-level and high-level features automatically without human guidance.

Subsequently, these extracted feature maps undergo transfer from the previous step to the Genetic Algorithm (GA).

The GA optimizes the selection of the most discriminative set of features using evolutionary computation procedures such as selection, cross-over, and mutation, hence reducing feature redundancy.

After optimization, the selected features are inputted to the bidirectional long short-term memory (Bi-LSTM) layer for contextual disease classification. The bidirectional aspect allows learning of all the relations between features by processing in both forward and backward directions.

Then comes the application of an attention mechanism to give importance to significant features while giving low importance to other background features not relevant to diseases.

The resulting features will be subjected to a dense fully-connected layer using softmax as its activation function for multiple disease predictions.

VII. RESULT ANALYSIS

The performance of the proposed Multi Disease The prediction through the Deep Learning (MDPDL) model is analyzed based on classification measures like Accuracy, Precision, Recall, F1-Score, and Confusion Matrix Analysis.

Such measures guarantee a thorough evaluation of the diagnostic efficiency considering several types of diseases.

The comparative study with other machine learning classifiers, for example, KNN, Naive Bayes, and SVM shows that classic techniques produce

techniques have produced rather poor results because of their inability to recognize deep spatial and contextual features of images in medical diagnostics. The proposed approach based on the use of CNN-GA-BiLSTM-Attention flipping demonstrates the classification accuracy of about 96%.



The reasons for performance enhancement include feature extraction enabled by hierarchical layers of CNN, the optimal selection of features using Genetic Algorithm, the treatment of contextual dependencies using Bi-LSTM, and adaptive feature refinement with help from attention mechanism. The confusion matrix determines that false positives and false negatives are markedly minimized in contrast to previous models.

Moreover, the system also exhibits excellent

generalization of the technique through various imaging techniques and disease categories.

DISCUSSION

Combining deep learning with evolutionary computation leads to substantial improvements in multi-disease classification processes. The CNN component manages to identify intricate pathological structures, which cannot be easily identified using traditional manual approaches for feature extraction. Through the use of GA, redundancies within the feature space are eliminated.

The Bi-LSTM classifier helps enhance context awareness through its bidirectional modeling capabilities of the extracted features, whereas the attention model enhances interpretability by emphasizing the disease-related region. Despite the increase in computational complexity due to the hybrid model design, it still allows efficient inference time for real-time applications.

Nevertheless, the accuracy of the model is affected by factors such as the number and diversity of images and their annotations. The larger and more diverse the data used, the better the accuracy and clinical relevance of the results.

VIII. CONCLUSION

In this paper, we have introduced a MDPDL system which uses a fusion of deep learning approaches such as CNN for feature extraction,

Genetic Algorithm for feature optimization, Bi-LSTM for context modeling, and attention mechanism for enhancing the output. This system performs significantly better in terms of diagnostic accuracy, achieving an accuracy of nearly 96%. In comparison to traditional machine learning approaches, our proposed MDPDL framework offers improved spatial representation learning, avoids redundant feature learning, enhances context modeling, and provides more accurate classification results.

IX. FUTURE WORK

Future developments of the MDPDL architecture will involve the use of Explainable AI methods like Grad-CAM for interpretability, severity scoring, deployment on the cloud, federated learning to facilitate joint training, and real-time diagnosis using mobile devices.

The proposed solution may be developed further by employing transfer learning as well as hybrid architectures including but not limited to ResNet, EfficientNet, and Vision Transformers (ViT) for better features' detection and classification. Additionally, the architecture can be extended with Explainable AI (XAI) to provide the rationale behind each prediction, making it clinically applicable.

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