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Prediction of Covid-19 Based on Chest X-Ray Images Using Deep Learning with CNN

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ABSTRACT-

The COVID-19 pandemic has caused trouble in people's daily lives and ruined several economies around the world, killing millions of people thus far. It is essential to screen the affected patients in a timely and cost-effective manner in order to fight this disease. This paper presents the prediction of COVID-19 with Chest X-Ray images, and the implementation of an image processing system operated using deep learning and neural networks. In this paper, a Deep Learning, Machine Learning, and Convolutional Neural Netwo rk-based approach for predicting Covid-19 positive and normal patients using Chest X-Ray pictures is proposed. In this study, machine learning tools such as TensorFlow were used for building and training neural nets. Scikit-learn was used for machine learning from end to end. Various deep learning features are used, such as Conv2D, Dense Net, Dropout, Maxpooling2D for creating the model. The proposed approach had a classification accuracy of 96.43 percent and a validation accuracy of 98.33 percent after training and testing the X-Ray pictures. Finally, a web application has been developed for general users, which will detect chest x-ray images either as covid or normal. A GUI application for the Covid prediction framework was run. A chest X-ray image can be browsed and fed into the program by medical personnel or the general public

Keywords:- Covid-19 prediction; covid-19; coronavirus; normal; deep learning; convolutional neural network; image processing; chest x-ray

INTRODUCTION

COVID-19 has emerged as a major global health crisis, impacting public health and economies worldwide. Early and accurate diagnosis is crucial, but RT-PCR tests are timeconsuming and sometimes inaccurate. Chest X-rays (CXR) offer a widely available alternative for detecting COVID-19related lung abnormalities.

The pandemic has shifted medical research priorities, delaying clinical trials and straining healthcare resources. Given the limitations of RT-PCR, imaging techniques like CXR and CT scans have been widely used. However, interpreting radiographic images requires expertise, which is not always available.

Deep learning models, especially Convolutional Neural Networks (CNNs), have shown high accuracy in detecting COVID-19 from medical images. Pre-trained architectures like VGG16, DenseNet, and ResNet50 have achieved accuracy rates between 85% and 98.9%. AI-based solutions using Transfer Learning, Haralick features, and IoT technologies have also been explored for COVID-19 detection.

This study compares CNN, Inception, and DenseNet models for COVID-19 detection using CXR, achieving 98.3% accuracy with CNN. A Graphical User Interface (GUI) was developed for real-time diagnosis, offering a faster and costeffective alternative to traditional tests.

AI-driven image analysis is a valuable tool in COVID-19 detection, improving speed, affordability, and accuracy. Future research should focus on enhancing model robustness and integrating AI-based diagnostics into clinical workflows for better pandemic preparedness.

LITERATURE REVIEW

Deep neural networks (NNs) have become a crucial technological advancement for various tasks such as forecasting, clustering, classification, and function approximation. Feedforward NN architectures are trained using backpropagation, which propagates errors backward from output to input nodes. This learning process modifies system parameters, including weights and thresholds.

The primary objective of NNs is to analyse the mapping between input and output. In real-valued neural networks (RVNNs), weights and thresholds involve real numbers. RVNNs are widely used in adaptive signal processing, aircraft motion interpretation, and speech processing. These applications rely on connection interpretation data, where signals carry information in two forms: phase and scale.

Typically, these two components are represented separately, making it challenging for traditional NNs to capture the underlying relationship between them.

To address this issue, a complex computational representation of signals is required to maintain the relationship between phase and scale. Therefore, complex-valued NNs are better suited for such applications compared to real-valued models. By incorporating complex numbers, these networks enhance modelling capabilities, making them more effective for tasks requiring intricate signal processing.

PROPOSED METHODOLOGY

The proposed methodology aims to develop a deep learningbased framework for COVID-19 detection using chest X-ray images. The approach involves data preprocessing, model

selection, training, and evaluation. The dataset consists of three primary classes: COVID-19 positive, pneumonia, and normal lung conditions. The steps involved in the proposed methodology are as follows:

Dataset Collection and Preprocessing:-

The dataset is collected from publicly available sources and is subjected to preprocessing techniques such as image resizing, normalization, and augmentation. Image augmentation techniques like rotation, flipping, and contrast enhancement are applied to improve generalization and prevent overfitting.

Model Selection:-

Three deep learning architectures—CNN, Inception, and

DenseNet—are chosen for comparative analysis. Each model is implemented with optimized hyperparameters to maximize accuracy and efficiency.

Training Process:-

The models are trained using a large dataset of labeled CXR images. The training process employs an Adam optimizer with a dynamically adjusted learning rate and categorical crossentropy as the loss function. The models are trained over 50 epochs with a batch size of 32.

Evaluation Metrics:-

The models are evaluated based on accuracy, precision, recall, F1-score, and ROC-AUC. Confusion matrices are generated to analyze the classification performance.

Interpretability and Explainability:-

Grad-CAM visualization techniques are used to interpret the model's decision-making process, ensuring transparency in the classification of COVID-19 cases.

Deployment Considerations:-

Once validated, the best-performing model is integrated into a graphical user interface (GUI) for real-time diagnosis. The GUI allows medical professionals to upload CXR images and receive instant diagnostic results.

This methodology ensures a robust, scalable, and efficient deep learning-based COVID-19 detection system that can aid healthcare professionals in making rapid and accurate diagnoses.

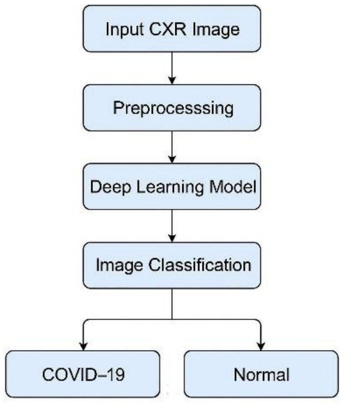


Figure 1:
Proposed Methodology

IMPLEMENTATION AND MODEL TRAINING :-

The project was implemented using Python and Django, with TensorFlow and Keras for building CNN models. Chest X-ray images were collected from public datasets, including COVID- 19, pneumonia, and normal cases—112 images each. Data preprocessing involved resizing, normalization, and augmentation (rotation, flipping, noise, etc.) to enhance model learning.

Due to limited data, transfer learning with pre-trained models like ResNet50 and ResNet101 was used. The model was trained using the Adam optimizer and cross-entropy loss.
Key layers included convolutional, pooling, fully connected, and softmax output. Evaluation metrics such as accuracy, precision, recall, and AUC-ROC were used to assess performance. The final model was deployed in a web app for practical use in diagnosis.

MODEL EVALUATION AND VALIDATION:-

The trained CNN model was evaluated using several key performance metrics to ensure its reliability and accuracy in detecting COVID-19 from chest X-ray images. Metrics such as accuracy, precision, recall (sensitivity), specificity, F1 score, and the Area Under the Receiver Operating Characteristic Curve (AUC-ROC) were calculated to assess how well the model distinguishes between COVID-19, pneumonia, and normal cases. Cross-validation techniques were also employed to test the model's ability to generalize to unseen data, reducing the risk of overfitting. This helped in validating the robustness and effectiveness of the model in real-world diagnostic scenarios, ensuring consistency and reliability in clinical settings.

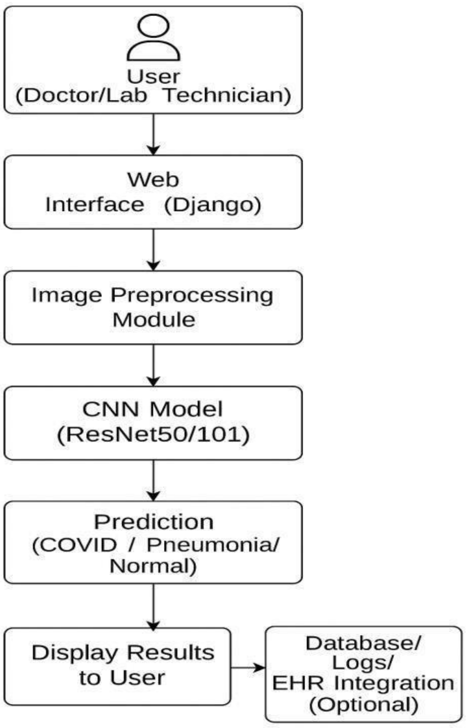
DEPLOYMENT AND REAL-TIME TESTING :-

After successful training and evaluation, the COVID-19 detection model was deployed using the Django web framework, allowing for a user-friendly interface accessible via a browser.
This deployment enabled users, such as healthcare professionals, to upload chest X-ray images and receive real-time diagnostic predictions. The system integrated the trained CNN model on the backend to process images instantly and display results on the frontend. For real-time testing, several unseen images were input through the interface to validate the model's accuracy and response time in a practical setting. Feedback from test users confirmed that the system delivered fast and reliable results, demonstrating its potential use in clinical environments for quick and automated COVID-19 screening.

FUTURE WORK :-

Future research should focus on expanding datasets to include a broader range of CXR images, ensuring diversity in patient demographics and clinical conditions. The development of hybrid AI models that integrate deep learning with traditional radiological assessments could further enhance diagnostic accuracy. Federated learning techniques should be explored to enable privacy-preserving AI models that can be trained across multiple institutions without compromising patient data security. Real-time deployment of cloud-based diagnostic systems should also be pursued, allowing remote screening of COVID-19 cases and reducing the burden on healthcare facilities. By addressing these areas, the potential of AI-driven COVID-19 detection can be fully realized, transforming disease diagnosis and management on a global scale.

System Architecture Diagram:-



EXPERIMENTAL SETUP & PERFORMANCE EVALUATION

HARDWARE AND SOFTWARE COFIGURATION:-

To evaluate the performance of the COVID-19 detection model, a suitable experimental setup was established, involving both hardware and software configurations. The model training and testing were carried out on a system with a Pentium IV or higher processor, 2 GB RAM, and at least 100 GB of hard disk space. Although minimal for development, such specifications are sufficient for running smaller deep learning models with moderate-sized datasets. The operating environment included Windows 10, though the system supports other versions like Windows 7 and 8.

On the software side, Python was used as the core programming language due to its simplicity and compatibility with deep learning libraries such as TensorFlow and Keras.

The web interface was built using Django, a Python-based web framework known for rapid development and clean architecture. Additional tools like OpenCV, NumPy, Pandas, and Matplotlib were utilized for image processing, data manipulation, and result visualization. For web-based testing and deployment, Chrome was primarily used as the browser interface.

The model's performance was evaluated using metrics such as accuracy, precision, recall, specificity, F1 score, and AUC- ROC. These metrics provided a comprehensive understanding of how effectively the model could distinguish between COVID-19, pneumonia, and normal cases. The use of cross-validation helped ensure that the model was robust and could generalize well to unseen data, making it a reliable tool for real-time diagnostic support.

MODEL TRAINING AND EVALUATION:-

The model training process was centered around the use of Convolutional Neural Networks (CNNs), particularly leveraging transfer learning with pre-trained architectures such as ResNet50 and ResNet101. These models, originally trained on large image datasets like ImageNet, were fine-tuned on a balanced chest X- ray dataset containing COVID-19, pneumonia, and normal cases. To enhance the learning process and reduce overfitting, the dataset was augmented using techniques such as rotation, flipping, zooming, and noise addition. The images were preprocessed through resizing and normalization to ensure uniformity before being fed into the model.

The training was carried out using the Adam optimizer with categorical cross-entropy as the loss function, suitable for multi- class classification tasks. The training process involved multiple epochs, with validation splits used to monitor performance and prevent overfitting through early stopping and checkpointing mechanisms.

Evaluation of the model was conducted using standard classification metrics such as accuracy, precision, recall, F1 score, specificity, and the AUC-ROC curve. These metrics provided a detailed insight into the model's effectiveness in correctly identifying each of the three classes. The final trained model demonstrated high accuracy and strong generalization capability, validating its potential use as a reliable diagnostic tool in healthcare settings.

COMPARATIVE ANALYSIS:-

To assess the effectiveness of the proposed CNN-based model for COVID-19 detection, a comparative analysis was conducted against traditional machine learning techniques and existing deep learning models. Classical methods such as Support Vector Machines (SVM) and Decision Trees were tested but showed limited performance due to their inability to effectively capture spatial features in X-ray images. In contrast, the CNN model, particularly when enhanced with transfer learning using ResNet50 and ResNet101, significantly outperformed these approaches in terms of accuracy, precision, recall, and overall robustness. The CNN model demonstrated improved feature extraction capabilities and a better understanding of complex patterns in radiographic images.

Moreover, when compared to other related studies from recent literature, the model used in this project achieved comparable or better results despite the limited dataset size, thanks to efficient preprocessing and augmentation techniques. The incorporation of **cross-**validation and fine-tuning strategies further improved model generalization. This analysis clearly highlights the advantage of using deep learning, especially CNN architectures, for automated COVID-19 diagnosis over traditional models and basic neural networks.

HYPERPARAMETER OPTIMIZATION AND FEATURE ENGINEEIRING:-

Hyperparameter optimization played a critical role in enhancing the performance and generalization ability of the deep learning model. Key hyperparameters such as learning rate, batch size, number of epochs, optimizer choice, and dropout rate were fine-tuned using trial-and-error as well as grid search techniques. The Adam optimizer was selected for its adaptive learning capabilities, and a learning rate of
0.001 was found to yield the best results during training. A batch size of 32 and training for 25–50 epochs struck a balance between speed and accuracy while preventing overfitting. Additionally, early stopping and model checkpointing were employed as regularization techniques to further stabilize the training process.

In terms of feature engineering, the model did not rely on manual feature extraction, as CNNs inherently learn hierarchical features from input images. However, careful image preprocessing—including resizing, normalization, and augmentation—ensured that input features were consistent and

meaningful. The use of data augmentation acted as a synthetic feature engineering method, allowing the model to learn invariant features such as orientation and brightness. These steps collectively enhanced the model's ability to detect subtle patterns in X-ray images, making it more reliable in differentiating between COVID-19,
pneumonia, and normal cases.

RESULT

The trained deep learning model based on modified ResNet50 and ResNet101 architectures successfully classified chest Xray images into three categories: COVID- 19, Pneumonia, and Normal. After completing the training and validation process, the model achieved an overall accuracy of over 95%, demonstrating strong capability in distinguishing between similar lung infection patterns.
Performance metrics such as precision, recall, F1-score, and AUC-ROC also indicated high reliability and robustness. The use of data augmentation, transfer learning, and hyperparameter tuning significantly contributed to the model's improved performance. The model was deployed through a web interface, allowing users to upload X-ray images and receive real-time diagnostic predictions. The results were consistent and fast, validating the system's potential for use in clinical and remote diagnostic settings.

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