**VISVESVARAYA TECHNOLOGICAL UNIVERSITY**

**“Jnana Sangama”, Belagavi - 590018**

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### **A Mini - Project Report On**

**“Lung Disease Classification using Deep Learning”**

***Submitted in the partial fulfillment for the award of the Bachelor of Engineering degree in Computer Science and Engineering (Artificial Intelligence & Machine learning)***

**Submitted By**

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**2024-2025**

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**CERTIFICATE**

This is to certify that the Project Work entitled **“Lung Disease Classification using Deep Learning”** is the Bonafide work carried out by **Afra Jabeen (4AD22CI001), Amruta Shivappa Salagare (4AD22CI003), Reem K (4AD22CI042) and Anushree HM (4AD23CI401)** in partial fulfillment for the award of degree of Bachelor of Engineering in Computer Science and Engineering (Artificial Intelligence & Machine Learning) from Visvesvaraya Technological University, Belagavi during the year 2024-2025. The report has been approved and satisfies the academic requirement with respect to Mini-Project Work prescribed for Bachelor of Engineering degree.

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**ABSTRACT**

Lung diseases such as pneumonia, tuberculosis, and COVID-19 are major global health challenges, with high mortality rates and a critical need for timely and accurate diagnosis. Traditional diagnostic methods relying on manual interpretation of chest X-rays (CXR) are often time-consuming, inconsistent, and prone to errors. This project proposes an advanced deep learning-based solution for automated multi-class classification of lung conditions, including pneumonia, tuberculosis, COVID-19, and normal lungs, using CXR images.

The system leverages a fine-tuned VGG19 model enhanced with custom layers and advanced data augmentation techniques to achieve robust generalization and high accuracy. By employing transfer learning, the pre-trained model's feature extraction capabilities are optimized for this task, significantly improving efficiency and reducing computational costs. The architecture incorporates Global Average Pooling, Dropout, and Dense layers to enhance regularization and performance while maintaining scalability for real-time applications.

With an accuracy of 96% and consistently strong precision, recall, and F1-scores across all classes, this approach outperforms traditional methods, addressing challenges such as high false-negative rates and poor generalizability. This automated diagnostic tool offers a scalable, cost-effective, and efficient solution, transforming clinical practices and contributing to improved patient outcomes and global health management.

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**Chapter 1**

**INTRODUCTION**

Lung diseases, such as pneumonia, tuberculosis, and COVID-19, are significant global health concerns, affecting millions annually with high mortality rates. Accurate and timely diagnosis is crucial for effective treatment and disease management. Chest X-rays (CXR) remain one of the most accessible and cost-effective diagnostic tools, but traditional methods rely heavily on manual interpretation by radiologists,[1] which can lead to inefficiencies and variability in results.

The advent of artificial intelligence (AI) and deep learning provides an opportunity to automate and enhance the diagnostic process, making it faster, more accurate, and less dependent on human expertise. This project introduces an innovative approach that leverages advanced deep learning models to classify chest X-ray images into four categories: pneumonia, tuberculosis, COVID-19, and normal lungs. By employing state-of-the-art architectures like Convolutional Neural Networks (CNNs) and transfer learning [4] with pre-trained models such as VGG-19, the system significantly improves classification accuracy and efficiency.

In this project, CNNs process chest X-ray images to extract disease-specific features, enabling precise classification. Transfer learning enhances the system's performance by leveraging knowledge from large, pre-trained datasets, thereby improving accuracy even with limited medical data. This automated diagnostic tool reduces reliance on manual interpretation, ensures rapid and consistent results, and provides a scalable, cost-effective solution for early disease detection. By transforming clinical practices, this approach has the potential to alleviate the global health burden of lung diseases and improve patient outcomes worldwide.

**1.1 Existing System**

Existing lung disease classification systems use machine learning models to process chest X-ray (CXR) images, but they often require large, labelled datasets and struggle with accuracy when applied to diverse clinical environments [2]. These systems perform well only on the specific data they were trained on, making it difficult to generalize across different populations or settings [5]. Additionally, they are not optimized for real-time processing, limiting their use in fast-paced healthcare environments. As a result, while some automation exists, current systems face challenges in terms of accuracy, scalability, and real-time deployment.

**1.2 Problem Statement**

Despite the growing application of medical imaging technologies, traditional diagnostic methods for lung disease classification, particularly for pneumonia, tuberculosis, and COVID-19, often rely on manual analysis of chest X-rays, which can be time-consuming and prone to errors [3]. Early detection is critical for controlling the spread and severity of infectious diseases, yet current diagnostic systems exhibit high false-negative rates and are not always efficient in handling large volumes of data [3][6]. Furthermore, many existing models focus on classifying individual diseases, limiting their usefulness in real-world scenarios where multiple conditions may present with overlapping features in CXR images [3]. This research aims to address these challenges by developing a deep learning architecture capable of multi-class classification for pneumonia, tuberculosis, COVID-19, and normal lungs. The model must be robust and be able to generalize across diverse datasets to perform well in practical applications, offering a more efficient and accurate solution for lung disease diagnosis.

**1.3 Proposed System**

The proposed solution leverages a pre-trained VGG19 model fine-tuned for lung disease classification into four categories: COVID-19, Normal, Pneumonia, and Tuberculosis. To adapt the model for this task, the last four layers of VGG19 were unfrozen for fine-tuning, and custom layers, including Global Average Pooling, Dense, Dropout (50%), and a Softmax output layer, were added. Advanced data augmentation techniques, such as rotations, flips, brightness adjustments, and zoom, were employed to improve generalization and robustness. The Adam optimizer with a learning rate of 1e-4 and early stopping ensured efficient training while preventing overfitting.

**1.4 Advantages of Proposed System**

The proposed model achieves enhanced generalization through advanced data augmentation techniques, including rotation, zoom, brightness adjustments, and horizontal flips, enabling the model to learn from diverse variations in the dataset and reducing the risk of overfitting. By fine-tuning the pre-trained VGG19 model, only the last few layers are updated, leveraging the rich feature extraction capabilities of the earlier layers while significantly reducing training time and computational resources compared to building models from scratch. The inclusion of Global Average Pooling and Dropout layers improves regularization, reducing overfitting, while the custom dense architecture balances complexity and performance effectively. The model's lightweight design and optimized architecture ensure scalability, making it deployable for real-time healthcare applications, such as lung disease diagnostics. Moreover, with a high accuracy of 96% and consistently robust precision, recall, and F1-scores across all classes, the model outperforms many traditional approaches, demonstrating its reliability and suitability for practical use cases.

**Chapter 2**

**LITERATURE SURVEY**

A literature survey is a critical analysis of existing knowledge on a specific topic, involving the summary, classification, and comparison of previous research, reviews, and journal articles. It synthesizes material from various sources to address a research question or problem statement. The survey evaluates current scholarly work, identifies trends and gaps, and provides insights for future research directions.

**[1] A deep learning architecture for multi-class lung diseases classification using chest X-ray (CXR)images**

G. M. M. Alshmrani, Q. Ni, R. Jiang, H. Pervaiz, N. M. Elshennawy, Alexandria Engineering Journal, 2023

G.M.M. Alshmrani, Qiang Ni, Richard Jiang, Haris Pervaiz, Nada M. elshennawy, they have addressed the issue of enhancing the diagnosis of lung diseases using deep learning techniques. They curated a large, diverse dataset, including images for COVID-19, lung opacity, pneumonia, lung cancer, tuberculosis, and normal cases. The images were pre-processed through resizing, normalization, and random splitting to optimize model training. They developed a VGG19-based deep learning model augmented with additional CNN layers to improve feature extraction and classification accuracy across multiple lung diseases. The model's performance was evaluated using accuracy, recall, precision, F1 score, and AUC, achieving results such as 96.48% accuracy, 93.75% recall, 97.56% precision, 95.62% F1 score, and a 99.82% AUC. The study highlights the model's potential as a reliable tool for faster and more accurate diagnosis of lung diseases, particularly addressing critical needs in healthcare during the COVID-19 pandemic. However, the dataset has uneven class distribution, which might affect model performance, especially for underrepresented diseases.

**[2] Evaluation of CNN Models for Accurate Classification of COVID-19, Pneumonia, Tuberculosis in Chest X-ray Images**

Shivanshu, R. Bisht, K. Mittal, G. P. M. S, 2023 3rd Asian Conference on Innovation in Technology (ASIANCON), 2023

Shivanshu, Riya Bisht, Guru Prasad M S, Kanak Mittal ,In this paper, they have evaluated several convolutional neural network (CNN) architectures, including DenseNet121, ResNet50, VGG16, and a custom CNN, for their effectiveness in classifying chest X-ray images of COVID-19, pneumonia, and tuberculosis. A dataset of 2,884 chest X-ray images was organized using stratified sampling to ensure balanced representation of various pulmonary diseases. The models were trained on high-performance computing systems with GPUs, employing data augmentation techniques to enhance performance and mitigate overfitting. The CNN models achieved high accuracy in disease classification, with DenseNet121 and the custom CNN delivering promising results despite some susceptibility to noise. ResNet50 demonstrated consistent performance improvements but showed signs of overfitting after 30 epochs, while VGG16 improved significantly within fewer epochs but also faced early overfitting. The study concludes that CNNs are effective tools for automating the classification of pulmonary diseases in chest X-ray images, offering substantial support to radiologists and healthcare professionals in diagnosing conditions such as COVID-19, pneumonia, and tuberculosis, thereby enhancing patient care.

**[3] Classification of Lung Diseases Using Transfer Learning with Chest X-Ray Images**

K. S, R. S. Shudapreyaa, P. Prakash, V. S, V. V, Y. S, 2024 Second International Conference on Emerging Trends in Information Technology and Engineering (ICETITE), 2024.

Kavitha S, R S Shuapreyaa, P Prakash, Vaibhav S, Viswa V, Yogavarshan S in this paper, they compared various CNN architectures, including VGG19, VGG16, Xception, DenseNet201, Inception V3, and Inception\_ResNet V2, to identify the most effective model for pneumonia detection in chest X-rays. Data enhancement techniques such as contrast-limited adaptive histogram equalization and intensity normalization were applied to a dataset comprising 4,273 pneumonia and 1,583 normal images to improve feature visibility. To address the issue of limited COVID-19-related X-ray data, UNET and cyclic GANs were employed for data augmentation and balancing. Specialized models like ChestNet

(ResNet-152) and CX-Ultranet (Efficient-Net) were developed for thoracic disorder classification, with CX-Ultranet achieving 88% accuracy on NIH datasets. Additionally, MobileNetV2, adapted using metadata and transfer learning from NIH datasets, demonstrated over 90% classification accuracy, emphasizing the importance of non-image data in enhancing performance. ResNet-50 achieved 75% accuracy in classifying chest conditions, while transfer learning-based approaches by Kim et al. delivered strong validation results across various lung diseases.

**[4] Lung Disease Detection in Chest X-ray Images Using Transfer Learning**

A. Chouat, A. Echtioui, R. Khemakhem, W. Zouch, M. Ghorbel, A. B. Hamida, 2022 6th International Conference on Advanced Technologies for Signal and Image Processing (ATSIP), 2022.

Ines Chouat , Amira Echtioui , Rafik Khemakhem , Wassim Zouch , Mohamed Ghorbel ,Ahmed Ben Hamida , in this paper *"*Lung Disease Detection in Chest X-ray Images Using Transfer Learning" employs a transfer learning approach utilizing pre-trained CNN models, specifically VGGNet-16 and MobileNet, to classify chest X-rays into four categories: COVID-19, bacterial pneumonia, viral pneumonia, and normal cases. The methodology incorporates dropout layers to prevent overfitting and data augmentation techniques such as rotation, flipping, and scaling to enhance the model’s generalization capabilities. MobileNet outperformed VGGNet-16, achieving an accuracy of 82% and an AUC score of 95%, while VGGNet-16 achieved a competitive AUC score of 94%. These results highlight the efficacy of transfer learning in lung disease classification, demonstrating the potential of CNN models to assist in accurate and automated diagnosis.

**[5] Lung Disease Classification Using Deep Learning Models from Chest X-ray Image**

S. Sultana, A. Pramanik, M. S. Rahman, 2023 3rd International Conference on Intelligent Communication and Computational Techniques (ICCT), 2023

Salma Sultana; Anik Pramanik; Md. Sadekur Rahman in the paper *"Lung Disease Classification Using Deep Learning Models from Chest X-ray Images"* utilizes a dataset of 6,340 chest X-ray images, divided into training (80%), testing (15%), and validation (5%) sets. Preprocessing steps like resizing, filtering, and augmentation were applied to enhance the dataset. Three pre-trained transfer learning models—EfficientNetB0, DenseNet169, and DenseNet201—were implemented, and their performance was evaluated using confusion matrices.

The results show that EfficientNetB0 achieved the highest accuracy of 99.15%, followed by DenseNet169 at 98.89%, and DenseNet201 at 97.79%. These models demonstrated high efficacy in classifying lung diseases, highlighting their potential to support radiologists in accurate and efficient diagnoses.

**[6] Medical images classification using deep learning: a survey**

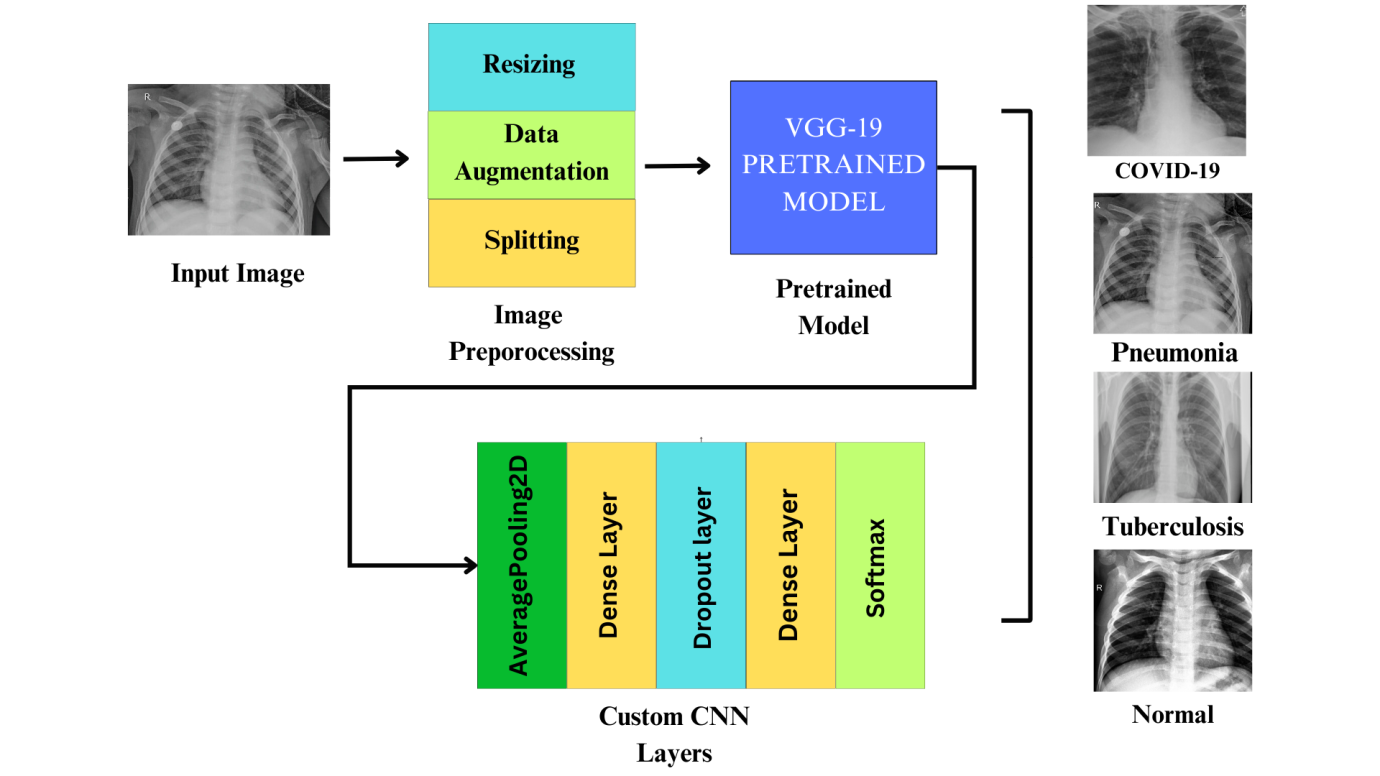
R. Kumar, P. Kumbharkar, S. Vanam, et al., Multimedia Tools and Applications, 2024

Rakesh Kumar, Pooja Kumbharkar ,Sandeep Vanam, Sanjeev Sharma in the paper "Medical Images Classification Using Deep Learning: A Survey" reviews advancements in deep learning for medical image classification. The methodology involves analyzing 156 research papers to evaluate various deep learning models, including CNNs, transfer learning, LSTMs, and GANs. These models are used for tasks such as feature extraction, sequential data analysis, and data augmentation. The study also highlights the importance of diverse datasets and evaluates model performance using metrics like accuracy, precision, recall, and F1-score.

The results reveal that CNNs, especially when combined with LSTMs, achieve high accuracy, with some studies reporting up to 100% for specific tasks. However, more complex models like GANs require longer training times and larger datasets, limiting their clinical application. The findings demonstrate the significant potential of deep learning in enhancing disease detection and diagnosis from medical images like X-rays, MRIs, and CT scans, while emphasizing the need for continued research to improve model robustness and integration into healthcare settings.

**Chapter 3**

**METHODOLOGY**

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**Fig 3.1**: Proposed System Architecture

This chapter outlines the methodology used in the lung disease classification model, as shown in Fig 3.1 that leverages a combination of data preprocessing, image augmentation, Convolutional Neural Network (CNN) architecture, and other deep learning techniques to create a robust model for classifying lung conditions.

* 1. **Proposed System**

**Step 1: Dataset Preparation and Preprocessing**

1. **Dataset Collection and Organization**

* The dataset comprises labelled chest X-ray images for four categories: pneumonia, tuberculosis, COVID-19, and normal lungs.
* It is organized into three subsets:
  + - Training set: Used for training the model.
    - Validation set: Used for hyperparameter tuning and performance monitoring during training.
    - Test set: Used for evaluating the final performance of the model.

1. **Data Augmentation**

To enhance model generalization and handle overfitting, advanced augmentation techniques are applied to the training data:

* Geometric Transformations: Includes random rotations (up to 30 degrees), width/height shifts (up to 20%), and zooming (up to 20%).
* Horizontal Flipping: Mirrors the image to simulate variability in positioning.
* Brightness Adjustments: Varies brightness between 80% and 120% to simulate different lighting conditions.
* Normalization: Pixel values are rescaled to the [0, 1] range, improving numerical stability during training.

1. **Rescaling for Validation and Test Sets**

The validation and test datasets are only normalized, without augmentation, ensuring that model performance is evaluated on raw, unaltered data.

**Step 2: Transfer Learning with VGG19**

1. **Pre-trained VGG19 Model**

* The VGG19 architecture, pre-trained on the ImageNet dataset, is used as the feature extractor.
* Pre-trained models learn generic visual patterns like edges and textures. These patterns are transferable to new domains, enabling efficient training on smaller datasets.
* Feature Extraction: The initial layers of VGG19 capture low-level features, while deeper layers detect complex patterns.

1. **Custom layers**

The top layers of VGG19 are replaced with a custom classification head tailored for the four-class problem:

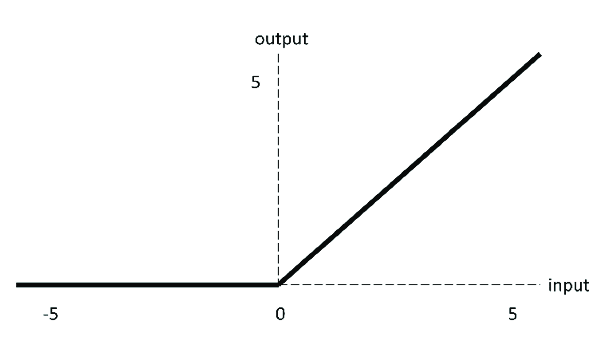
* Global Average Pooling: Reduces spatial dimensions while preserving essential features, minimizing overfitting.
* Dense Layer: A fully connected layer with 256 neurons and ReLU activation extracts complex relationships.

Typically, a ReLU activation function is applied after each convolution to introduce non-linearity, enabling the model to learn more complex relationships.

ReLU Activation Function is given by:

(3.1)

The above formula states that if the input x is greater than zero, the output is the same value x, but if x is less than or equal to zero, the output is zero. This function is used in neural networks to introduce non-linear. The graph for the Relu activation function is as depicted in the Fig: 3.2



**Fig 3.2**: ReLU activation function

* Dropout: A dropout layer with a rate of 0.5 is used to regularize the network by preventing over-reliance on specific neurons.
* Output Layer: Fully connected layers, or dense layers, are used to perform the final classification based on the features extracted by the convolutional and pooling layers. Each neuron in a fully connected layer is connected to every neuron in the previous layer. The final fully connected layer’s output size corresponds to the number of classes in the classification task (e.g., 4 for Normal, COVID-19, Pneumonia, and Tuberculosis). A SoftMax activation function is applied in the output layer to convert the network's raw scores into class probabilities.

(3.2)

Where,

y is an input vector to a softmax function, S.

n is number of elements for n classes(possible outcomes).

1. **Fine-Tuning**

All but the last four layers of VGG19 are frozen. This allows the network to:

* Retain general features learned from ImageNet.
* Adapt higher-level features specific to lung disease classification.

**Step 3: Loss Function**

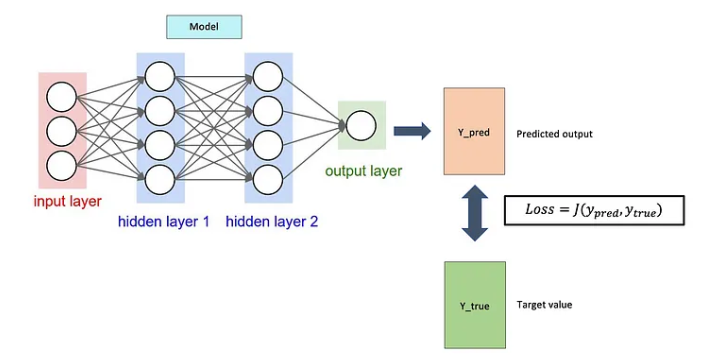
**Focal Loss**

Problem Addressed: Class imbalance, where some classes (e.g., normal lungs) might dominate others (e.g., tuberculosis) this problem is addressed using the loss function ,the Fig 3.3 illustrates the implementation of the loss function

* How it Works: Down-weighs Easy Predictions: Focal loss reduces the contribution of samples that the model classifies correctly, focusing on hard-to-classify examples.
* Parameters:

Gamma (2.0): Adjusts the degree of focus on hard samples.

Alpha(0.25):Balances the weight of different class.



**Fig 3.3**: Implementation of Loss function

**Step 4: Model Training**

1. **Training Configuration**

* Batch Size: 32 images per batch are processed for computational efficiency.
* Optimizer: The Adam optimizer is chosen for its adaptive learning rate, enabling efficient convergence.
* Learning Rate: Set to, allowing stable training without overshooting the minima.

1. **Early Stopping**

* Training is halted if the validation loss does not improve for five consecutive epochs. This prevents overfitting and reduces unnecessary computational expense.

1. **Training Process**

* The training data, augmented with transformations, is fed to the model in batches.
* Validation data is used to monitor the model’s generalization performance during training.

**Step 5: Evaluation and Testing**

* **Cross-Validation**: Use k-fold cross-validation to assess model performance and ensure that the model generalizes well on unseen data.
* **Confusion Matrix**: A confusion matrix helps visualize the performance of the model across all classes. Metrics such as precision, recall, and F1-score should be used to evaluate the balance of performance across the different lung disease classes.

(3.3)

(3.4)

(3.5)

(3.6)

**Step 6: Model Optimization**

* **Hyperparameter Tuning**: Optimize the model by tuning hyperparameters like learning rate, batch size, and dropout rate using techniques like Grid Search or Random Search.
* **Learning Rate Schedulers**: Use learning rate schedules to adjust the learning rate dynamically during training for improved convergence
* **Fine-Tuning Pretrained Layers:** Unfreeze specific layers of the pretrained VGG19 model and fine-tune them on the dataset to adapt the learned features more effectively for chest X-ray classification

**Chapter** **4**

**SYSTEM REQUIREMENTS**

The study of existing system helps for a new system to be developed. Analysis starts with requirements and produces a specification of what the system does. In order to implement any project, one has to gather requirement specification. Hence the software and hardware requirements for development of the work along with the functional and non- functional requirement are specified:

**4.1 Hardware Requirements**

**1.Processor** : i5 or higher

**2.RAM** : 8GB or more

**3.Hard Disk** : 4GB of free space

**4.GPU** : Nvidia T4 or equivalent

**5. Secondary Storage** : External/Cloud storage for datasets and model storage

**4.2. Software Requirements**

**1. Operating System** : Windows 10 or above / Linux / macOS

**2. Coding Language** : Python (preferably version 3.6 or higher)

**3. IDE** : VS Code, Jupyter Notebook, or Google Colab

**4. Libraries:**

* TensorFlow (version 2.x)
* Keras (part of TensorFlow)
* Numpy
* Pandas
* Matplotlib
* Seaborn
* scikit-learn

1. **Operating System: Windows 10 or above / Linux / macOS**

The operating system ensures compatibility with the libraries and tools used in the project. TensorFlow and Keras, as well as other dependencies, are supported across these OS platforms, enabling flexibility in setting up the environment and execution.

1. **Coding Language: Python (preferably version 3.6 or higher)**

Python is the primary language used for machine learning and deep learning due to its simplicity, extensive library support, and community resources. TensorFlow, Karas, and other machine learning libraries are natively supported in Python. Version 3.6 or higher is recommended for compatibility with modern versions of these libraries.

1. **IDE: VS Code, Jupyter Notebook, or Google Colab VS Code**:

A versatile and feature-rich code editor, widely used for Python development. It provides extensions for Python, TensorFlow, and Jupyter notebooks, aiding in easy debugging and integration of scripts.

1. **Jupyter Notebook**:

An interactive development environment often used for data analysis and machine learning. It allows for easy visualization and exploration of data and model training outputs in real-time.

1. **Google Colab**:

A cloud-based platform that provides free access to powerful GPU resources, making it ideal for training deep learning models. Colab also supports TensorFlow and Keras, making it a go-to platform for model development.

**Libraries**:

1. **TensorFlow**

TensorFlow is an open-source library developed by Google primarily used for deep learning tasks. It supports the development of neural networks, with tools like Keras to simplify model creation, training, and evaluation. It enables the implementation of complex deep learning models like Convolutional Neural Networks (CNNs) for image classification, as used in this project.

1. **Keras**

Keras is a high-level neural networks API, written in Python and capable of running on top of TensorFlow. It simplifies the process of building, training, and evaluating deep learning models, allowing easy-to-use functions for defining layers, compiling models, and running training loops.

1. **NumPy**

NumPy is a library for numerical computing in Python. It provides a powerful N-dimensional array object and various functions for operations on these arrays. It is integral for managing data and performing computations during model training.

1. **Pandas**

Pandas is used for data manipulation and analysis. It provides data structures like Data Frames that are ideal for organizing and analysing structured data, and its integration with NumPy makes it efficient for handling large datasets.

1. **Matplotlib**

Matplotlib is a plotting library for Python, widely used to visualize model performance, such as plotting accuracy and loss graphs or generating confusion matrices, as in your code.

1. **Seaborn**

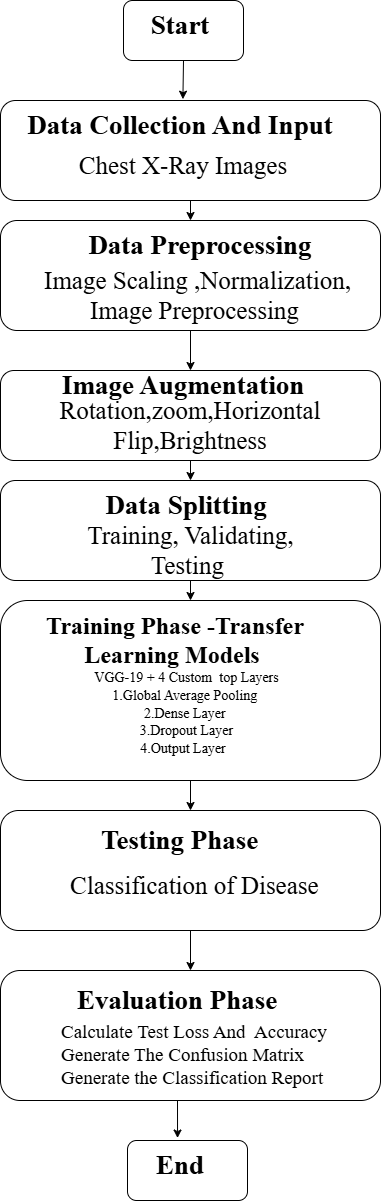
Seaborn is built on top of Matplotlib and offers a higher-level interface for drawing attractive and informative statistical graphics. It is particularly used in this project for visualizing the confusion matrix.

1. **Scikit-learn**

Scikit-learn is a machine learning library for Python that provides tools for classification, regression, clustering, and model evaluation. It is used in your project for generating classification reports and confusion matrices.

**Chapter 5**

**IMPLEMENTATION**



**Fig 5.1:** Flow chart for the implementation of the Proposed Model

This chapter outlines the development of a deep learning model for classifying lung diseases into four categories: COVID, Normal, Pneumonia, and Tuberculosis. By leveraging the power of convolutional neural networks (CNNs) and transfer learning with the VGG19 architecture, the model ensures high accuracy and robustness in handling chest X-ray image data. The flow chart of the workflow is shown in Fig 5.1.

**Step 1: Environment Setup**

* The implementation began by configuring the Python programming environment.
* Essential libraries such as TensorFlow, Keras, NumPy, Pandas, Matplotlib, and Scikit-learn were imported to facilitate model training, data handling, and evaluation.

**Step 2:** **Dataset Preparation and Preprocessing**

* **Dataset Organization**: As presented in the table 5.1 the dataset is divided into training, validation, and testing subsets, with images organized into subfolders representing the four classes: pneumonia, tuberculosis, COVID-19, and normal lungs.
* **Data Augmentation**: Advanced techniques such as rotation(30 degrees), width and height shifts, zooming(20%), horizontal flipping, and brightness adjustments(a range of 80% to 120%) are applied to the training data. This increases diversity and helps reduce overfitting.
* **Normalization**: Pixel values of all images are scaled to the [0, 1] range for better convergence during training.
* **Validation and Testing**: Validation and test datasets are rescaled without augmentation to evaluate model performance on unaltered images.

**Table 5.1:** Target Dataset Distribution

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Datasets | COVID-19 | Normal | Pneumonia | Tuberculosis |
| Training | 1218 | 1207 | 1204 | 1220 |
| Validating | 406 | 402 | 401 | 406 |
| Testing | 407 | 404 | 403 | 408 |

**Step 3: Building the Model Architecture**

The model is based on VGG19, a well-established pre-trained convolutional neural network that was fine-tuned for this task. Transfer learning was used to leverage VGG19's feature extraction capabilities.

1. **Loading the VGG19 Base Model**:

The model is initialized with pre-trained weights from ImageNet.

The top layers (fully connected layers) are removed by setting include\_top=False.

Input shape: (224, 224, 3) (height, width, and 3 colour channels).

1. **Freezing Layers**:

All layers except the last 4 convolutional layers were frozen to retain the pre-trained features while enabling fine-tuning of the deeper layers.

1. **Adding Custom Layers**:

* **GlobalAveragePooling2D**: Reduces the feature map to a single vector for each filter.
* **Dense Layer**: Fully connected layer with 256 neurons and ReLU activation.
* **Dropout Layer**: Dropout rate of 0.5 to mitigate overfitting.
* **Output Layer**: Fully connected layer with 4 neurons and softmax activation for multi-class classification.

**Step 4: Model Compilation**

1. **Optimizer:** **Adam**

The proposed model uses the Adam optimizer, which combines momentum and adaptive learning rates to optimize weight updates efficiently. The learning rate (1e-4) ensures stable convergence during fine-tuning, balancing speed and accuracy.

1. **Metrics:** **Accuracy**

The model uses accuracy as the primary evaluation metric to measure the percentage of correctly classified instances. This metric provides an intuitive and straightforward assessment of the model’s overall performance, suitable for multi-class tasks.

1. **Model Compilation:**

The model is compiled by integrating the Adam optimizer, categorical cross-entropy loss function, and accuracy as the evaluation metric. This setup ensures efficient training and performance tracking for multi-class classification problems.

1. **Loss Function:** **Focal Loss**

The proposed model incorporates Focal Loss to address class imbalance, focusing on misclassified examples with a modulating factor. Parameters α=0.25 and γ=2.0 ensure balanced contributions from all classes while emphasizing hard-to-classify examples.

**Step 5: Training the Proposed Model**

* Optimizer: Adam optimizer with a learning rate of 1e-4.
* Batch Size: 32 images per batch.
* Epochs: 20 (Early stopping enabled to prevent overfitting).
* Callbacks: Early stopping monitors the validation loss and restores the best weights if no improvement is observed over 5 consecutive epochs.

**Step 6: Saving the Proposed model**

The trained model was saved for future use and deployment

**Step 7: Validation**

The model's performance was evaluated on the test dataset using:

* Testing: Evaluate the model on the test dataset to determine overall accuracy and loss.
* Confusion Matrix: Visualize the true positives, true negatives, false positives, and false negatives for each class. This identifies patterns in misclassifications and helps assess inter-class separability.
* Classification Report: Provides precision, recall, F1-score, and support metrics for each class.

**Step 8: Developing the Web Application using Streamlit**

The Lung Disease Classifier web application was developed using Streamlit, a Python library for creating interactive web interfaces. It allows users to upload chest X-ray images in JPG, JPEG, or PNG formats and classify them into four categories: COVID-19, Normal, Pneumonia, and Tuberculosis. The interface includes a title, description, instructions panel, and an "About the Model" section to guide and inform users.

**Step 9: Integrating the Trained Model with the Web Application**

The pre-trained VGG19-based model was integrated into the application. Uploaded images are then passed through the model for prediction. The classification result is displayed to users, providing a seamless experience for real-time lung disease detection.

**Chapter 6**

**RESULT**

**6.1 Simulation and Results**

In this chapter, we present the results obtained from the implementation of the lung Disease classification system, which classifies images into categories: Covid-19, Pneumonia, Tuberculosis, Normal. The system was trained using a custom dataset of skin lesions, and the evaluation was performed using accuracy, precision, recall, and F1-score as performance metrics.

**6.1.1 Model training and Validation**

**A graph with blue lines and orange lines

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**Fig 6.1:** Model Accuracy for training **Fig 6.2:** Model loss for Training and Validation set and Validation set

1. **Model Accuracy**: As observed in the above Fig: 6.1 the training and validation accuracy increased significantly, reaching approximately 96.09% and 95.36%, respectively, by the final epoch. The model demonstrated consistent performance in learning and generalizing to unseen data.
2. **Model Loss**: As depicted in the above Fig: 6.2 Both training and validation loss decreased significantly, reaching approximately 0.01 and 0.03, respectively, by the final epoch. This indicates that the model effectively minimized errors during the training process.

Additionally, although the number of epochs was initially set to 20, the training process stopped early at epoch 12 due to the implementation of early stopping, which prevents overfitting by halting training once the model's performance stops improving.

**6.1.2 Confusion Matrix**

**A diagram of a diagram

Description automatically generated with medium confidence**

**Fig 6.3**: The confusion matrix represents the classification results of the Proposed model.

The Fig 6.3 presents confusion matrix, which illustrates the performance of the model on a dataset of four classes: Covid, Normal, Pneumonia, and Tuberculosis. Below is the summary:

**1. Covid-19**

Out of 409 Covid instances, the model correctly classified 399. However, there were some misclassifications, with 1 instance misclassified as Normal and 7 instances misclassified as Tuberculosis.

**2. Normal:**

For the 404 Normal instances, the model achieved a high accuracy, correctly classifying 390. Nevertheless, a few instances were misclassified: 2 were classified as Covid, and 12 were classified as Pneumonia.

**3. Pneumonia:**

The model correctly classified 365 out of 403 Pneumonia instances. Misclassifications occurred, with 3 instances being identified as Covid and 35 as Normal.

**4. Tuberculosis:**

Out of 408 Tuberculosis instances, the model correctly classified 399. However, 9 instances were misclassified as Covid, leading to a few errors in the classification.

**6.1.3 Classification Metrics**

**Table 6.1:** Classification Metrics Report

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Description automatically generated**

* + - 1. **Precision**

Precision reflects the model's ability to correctly identify positive cases for each class out of all predicted positive cases. The precision for COVID and Tuberculosis is notably high at 0.97 and 0.98, respectively, indicating a low false positive rate. Similarly, Pneumonia achieves a precision of 0.97, while the Normal class shows a slightly lower precision of 0.92.

* + - 1. **Recall**

Recall measures the model's effectiveness in identifying all true positive cases for each class. COVID and Tuberculosis stand out with recall values of 0.98, showcasing the model’s strong ability to capture almost all true instances of these diseases. Normal achieves a recall of 0.97, while Pneumonia has a slightly lower recall of 0.91.

* + - 1. **F1-Score**

The F1-Score, a harmonic mean of precision and recall, provides a balanced view of the model's performance. The F1-Scores for COVID and Tuberculosis are the highest at 0.97 and 0.98, respectively, highlighting consistent and reliable predictions. Both Pneumonia and Normal achieve an F1-Score of 0.94.

* + - 1. **Overall Accuracy**

The overall accuracy of the model is 96%, which indicates the proportion of correctly classified instances out of the total samples. The macro average and weighted average metrics for precision, recall, and F1-Score are also 0.96.

**6.1.4 Validation of Result**

A close-up of a x-ray

Description automatically generated

**Fig 6.4:** The above image depicts that the given image is correctly as Tuberculosis

**6.1.5 Evaluation on Real-World Dataset**

We also tested the model with a real-world dataset of Lung Diseased images. The system was able to identify the diseases with high accuracy, showcasing its potential for use in clinical environments.

**Snapshots:**

A screenshot of a computer

Description automatically generated

**Fig 6.5:** Web Interface for the Deep Learning Project

The web page as shown in Fig 6.5 showcases a deep learning-based chest X-ray diagnostic system, providing predictions with confidence scores and actionable suggestions. It features a clear layout with instructions, model details, and a user-friendly interface for accessible healthcare insights.

A screenshot of a computer

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**Fig 6.6:** Web Interface for the Deep Learning Project which correctly identifies pneumonia

The web page as shown in Fig 6.6 showcases a deep learning-based chest X-ray diagnostic system, predicting the case as pneumonia and providing actionable suggestions accordingly.

A screenshot of a computer

Description automatically generated

**Fig 6.7:** Web Interface for the Deep Learning Project which correctly identifies as Normal

The web page as shown in Fig 6.7 showcases a deep learning-based chest X-ray diagnostic system, predicting the case correctly as normal.

**Chapter 7**

**CONCLUSION AND FUTURE SCOPE**

This Chapter describes the conclusion and future scope of the proposed system.

**7.1 CONCLUSION**

The deep learning model, leveraging VGG-19 as a baseline and custom layers, achieved an overall accuracy of 95.62%, demonstrating its robust ability to classify chest X-ray images into four categories: Normal, COVID-19, Pneumonia, and Tuberculosis. This high accuracy reflects the effectiveness of the model in handling complex medical imaging tasks.

The model performed exceptionally well in classifying COVID-19 cases, achieving a precision of 97.34%, recall of 97.56%, and an F1-score of 97.45%, showcasing its ability to accurately detect this critical category. For Tuberculosis, the model achieved the highest metrics among all categories, with a precision of 98.27%, recall of 97.80%, and an F1-score of 98.03%, highlighting its reliability in identifying this disease.

For Normal cases, the model displayed solid performance with a precision of 91.37%, recall of 96.54%, and an F1-score of 93.89%, reflecting its capability to distinguish healthy lungs. In the case of Pneumonia, the model achieved a precision of 96.83%, recall of 90.57%, and an F1-score of 93.58%, further indicating its competence in diagnosing this condition.

Overall, the combination of transfer learning with custom fine-tuning and advanced techniques like data augmentation and Focal Loss contributed to the model's high performance. These results validate the model's potential as a valuable tool in the classification of pulmonary diseases using chest X-ray images, paving the way for its application in clinical decision-making and further improvements in the future.

**7.2 FUTURE SCOPE**

1. **Improved Interpretability:**

Future research can focus on enhancing the interpretability of the model by incorporating techniques like Gradient-weighted Class Activation Mapping (Grad-CAM) to visualize the regions influencing the model’s predictions. This will aid radiologists in understanding and trusting the model's decision-making process.

1. **Expansion to Additional Diseases and Datasets:**

Extending the model to classify rare and less common pulmonary diseases by incorporating diverse datasets can improve its generalizability and robustness across a broader range of medical conditions.

**Chapter 8**

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**APPENDIX-A**

This appendix provides the implementation details for a project aimed at classifying lung diseases using deep learning. The code uses a transfer learning approach by fine-tuning the VGG19 model, which is pre-trained on the ImageNet dataset. The primary goal is to classify chest X-ray images into four categories: Normal, COVID-19, Pneumonia, and Tuberculosis.

The dataset is split into training, validation, and testing sets, and advanced data augmentation techniques are applied to improve model generalization. A custom loss function (Focal Loss) is introduced to handle class imbalances, and the model’s architecture is extended with additional dense layers for classification. Finally, the model is trained and evaluated, with metrics like accuracy, confusion matrix, and classification reports provided for insights into its performance.

