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Deep Neural Network-Based Ct Scan Analysis For Lung Disease Detection In Diabetic Patients

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Abstract
Lung disease diagnosis in diabetic patients poses a significant challenge due to the complex and overlapping patterns observed in CT scan images. These scans often exhibit a wide range of pulmonary surface abnormalities, making it difficult for radiologists to distinguish between various lung diseases accurately. This research proposes a novel deep learning-based approach for the automated detection and classification of lung diseases in diabetic individuals using Deep Neural Networks (DNN). The study focused on the identification of diabetic stages using fundus images and integrates this diagnostic insight with pulmonary analysis to improve disease detection efficiency.The proposed system employs a DNN-based classifier trained on annotated CT scan images that have been validated by certified radiologists. The classifier not only analyzes lung images for disease patterns but also correlates them with the severity of diabetes, offering a comprehensive diagnostic model. Uniquely, the system takes the fundus image of a diabetic patient as an input to estimate the diabetes level and, based on that, predicts the likelihood and extent of associated lung diseases. This approach enhances early detection and allows for disease stratification based on diabetic stages. The model demonstrates high accuracy in detecting a variety of lung diseases commonly seen in diabetic patients, including asthma, pneumothorax or atelectasis, bronchitis, chronic obstructive pulmonary disease (COPD), lung cancer, and pneumonia. Its rapid image processing and low classification error make it suitable for large-scale, real-time screening applications. Designed with mass screening in mind, this DNN-based classifier has the potential to assist clinicians and healthcare providers in early intervention and treatment planning, particularly in resource-constrained settings where specialist radiologists may not be readily available.
Keywords - *Diabetic, Deep Neural Networks, CT scan lung images, fundus image, radiologist, image recognition, and lung diseases.*

INTRODUCTION

Lung disease in diabetic patients represents a growing concern in modern medicine due to the increased vulnerability of diabetic individuals to various pulmonary complications. Diabetes mellitus, a chronic metabolic disorder, contributes to systemic inflammation, impaired immune responses, and vascular abnormalities, which in turn increase the risk of respiratory illnesses. Recent clinical studies have shown a statistically significant association between diabetes and respiratory diseases such as asthma, chronic obstructive pulmonary disease (COPD), bronchitis, pneumonia, and lung cancer [1]. Detecting such diseases at early stages, particularly in diabetic populations, can drastically improve patient outcomes and reduce mortality rates. However, the diagnostic process is complicated by the high variability and complexity of lung surface patterns seen in computed tomography (CT) scans. CT imaging has become an essential modality for visualizing detailed anatomical structures within the lungs. While highly informative, the interpretation of CT images demands a high level of expertise and is often subject to human error, especially when dealing with complex or subtle abnormalities. In diabetic patients, lung tissues may present mixed features due to overlapping manifestations of infection, inflammation, or neoplastic changes, which makes accurate differentiation particularly difficult. Manual diagnosis in such scenarios is both time-consuming and prone to inconsistencies [2]. Therefore, developing automated, intelligent systems capable of accurately analyzing CT images and providing reliable diagnostics is a pressing necessity. Artificial Intelligence (AI), particularly Deep Neural Networks (DNN), has gained significant attention in recent years for its remarkable performance in visual pattern recognition tasks. DNNs have been successfully applied in a wide range of medical image analysis applications, including tumor detection, retinal disease classification, and skin lesion identification [3,4]. Their ability to learn complex representations from large datasets allows for superior accuracy and generalization compared to traditional machine learning methods. Specifically, DNNs have been proven effective in segmenting and classifying thoracic diseases from chest CT and X-ray images [5]. This research leverages the strength of DNNs to detect and classify multiple lung diseases in diabetic patients using CT scan images.In this study, we propose a DNN-based classifier system for the diagnosis of lung diseases in diabetic patients, incorporating both fundus images and CT scans as input modalities. The fundus image is used to determine the diabetic stage, which informs the severity model for lung disease prediction. The novelty of this research lies in its multimodal approach: fusing diabetic-related retinal pathology with pulmonary image data to improve disease-specific classification accuracy. This interdisciplinary strategy aims to mimic a holistic diagnostic approach, as an experienced clinician might consider comorbid indicators when forming a diagnosis.The CT images used for training and validation in this study were annotated by certified radiologists to ensure clinical relevance and ground-truth reliability. Diseases targeted in this work include asthma, pneumothorax or atelectasis, bronchitis, COPD, pneumonia, and lung cancer—ailments frequently observed among diabetic populations. The classifier demonstrates high performance in terms of detection speed, accuracy, and sensitivity across disease categories. This system is envisioned to support mass screening programs, particularly in under-resourced healthcare settings where access to skilled radiologists is limited. Recent studies have explored similar applications of DNNs in medical image analysis, including the development of lightweight neural architectures for rapid screening [6], the use of attention-based models for CT scan segmentation, and multimodal diagnostic systems integrating clinical and image data. However, to our knowledge, no prior work has explicitly integrated diabetic stage identification via fundus images with CT-based lung disease classification. This fusion makes the proposed model not only innovative but also clinically grounded.This paper is organized as follows: Section 2 reviews the related works in lung disease classification and diabetic diagnostics using deep learning. Section 3 describes the proposed DNN-based classifier system. Section 4 discusses the results and implications. Section 5 concludes the paper with future research directions.

2. Related works

Zhang et al. [7] propose a hybrid framework that integrates clinical information, CT radiomics, and deep learning features for the accurate prediction of invasive pulmonary aspergillosis. This fusion-based model improves diagnostic confidence, especially in immunocompromised patients, by utilizing deep representations from radiological imaging and correlating them with patient-specific clinical data, thus enabling early and precise detection. Mileto et al. [8] demonstrate that deep learning reconstruction significantly enhances the accuracy of pulmonary nodule detection and measurement in ultra-low-dose CT imaging. Their approach addresses the trade-off between radiation exposure and image quality, enabling safer and more accurate lung cancer screenings through improved sensitivity and reduced inter-reader variability. Nguyen, Zhang, and Ma [9] introduce a Transformer-based deep learning architecture for lung disease segmentation in CT images. Unlike traditional CNN-based models, the proposed framework captures long-range dependencies and contextual features, yielding superior performance in segmenting complex lung structures and disease regions, especially in heterogeneous thoracic CT scans. Ait Nasser and Akhloufi [10] provide a comprehensive review of recent deep learning models for chest disease detection using radiographic imaging, including X-rays and CT scans. They highlight the progression from basic CNN models to advanced attention and ensemble-based methods, offering insights into the comparative performance, challenges, and future directions of AI-assisted pulmonary diagnosis. Shahad A. Salih et al. [11] review several deep learning-based diagnostic systems for lung diseases and emphasize their roles in clinical decision support. They particularly focus on CNN and hybrid models that have been implemented in pneumonia, tuberculosis, COVID-19, and lung cancer detection, analyzing datasets, model training strategies, and deployment feasibility in clinical practice. Salih, Lu, and Qian [12] evaluate the effectiveness of deep learning on CT images for diagnosing severe pulmonary infections. Their model leverages image pre-processing and CNN-based classification to distinguish between infection severity levels. The study supports the growing use of AI in emergency diagnostics, especially for intensive care monitoring.

Qi et al. [13] present Lung-PNet, a deep learning model tailored to detect invasive adenocarcinoma within pure ground-glass nodules on chest CT scans. Their model outperforms radiologists in distinguishing invasive from non-invasive lesions, paving the way for improved early lung cancer management and surgical planning. Wang et al. [14] explore deep learning applications in interstitial lung disease (ILD), focusing on classification accuracy and prognostic prediction. Their system combines CT features with longitudinal data to estimate patient outcomes, demonstrating the potential of AI in personalized medicine and chronic respiratory condition management. Sharkey et al. [15] propose an automated deep learning pipeline for quantifying lung disease in patients with pulmonary hypertension using CT pulmonary angiography. The system supports clinical assessments by offering consistent, objective measurements of disease burden and vascular remodeling, significantly aiding in treatment planning. Mamun et al. [16] introduce LCDctCNN, a CNN-based model for diagnosing lung cancer from CT images. The proposed system emphasizes lightweight computation while achieving high classification accuracy, making it viable for deployment in resource-constrained healthcare environments or mobile diagnostic platforms. Abunajm et al. [17] design a deep learning framework aimed at early-stage lung cancer detection, particularly focusing on smaller nodules that are challenging to detect. By combining residual learning and dense connections, the model achieves robust generalization, making it suitable for early screening programs and follow-up imaging. Interdisciplinary researchers [18] develop a machine learning-based model that combines CT radiomics and clinical features to predict post-COVID pulmonary fibrosis. Their approach not only identifies fibrotic progression but also provides insights into high-risk patient profiling, aiding clinicians in managing long-term respiratory complications of COVID-19.

3. Proposed Methodology

The proposed model utilizes both fundus images and lung CT images as inputs and operates through a three-stage pipeline for disease classification. In the first stage, a Gaussian filter is applied to remove noise from the input images, enhancing image quality for further processing. In the second stage, the denoised images undergo segmentation using a fuzzy clustering technique to accurately isolate the infected regions. In the third stage, Gray-Level Co-occurrence Matrix (GLCM) features are extracted from the segmented regions to capture texture-based patterns relevant to disease diagnosis. Finally, a Deep Neural Network (DNN) is employed to train on these features and classify the diabetic patient's lung condition into one of four categories: Type 1 – Emphysema, Type 2 – Ground-Glass Opacity, Type 3 – Fibrosis, and Type 4 – Micronodules. Figure 1 depicts the architecture of the proposed model.

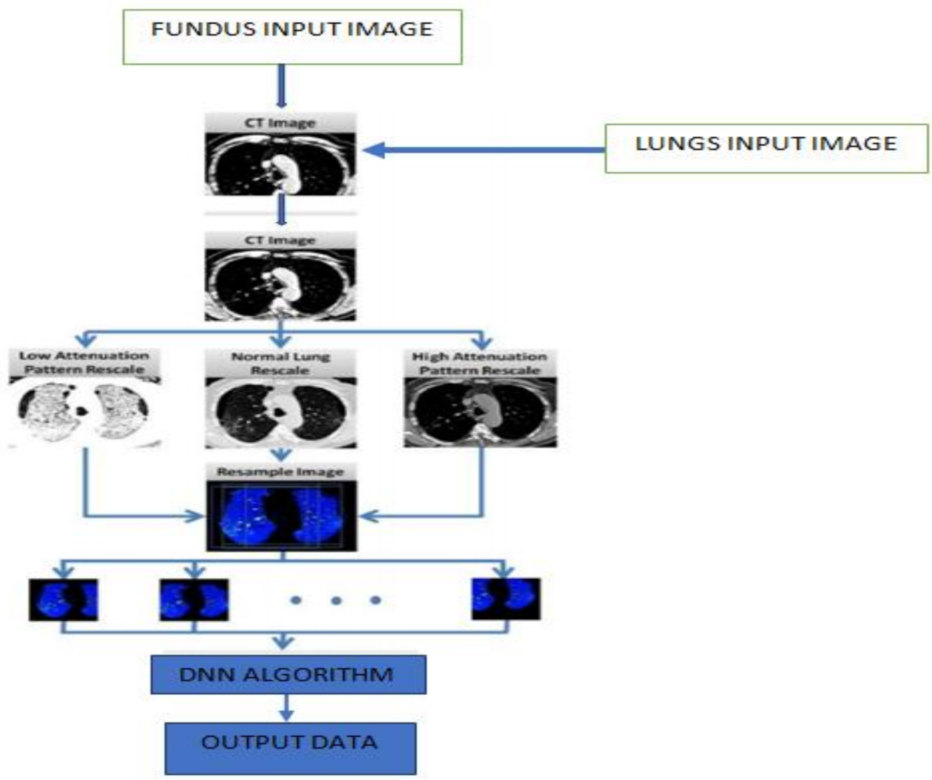


Figure 1. The block diagram of the proposed model

3.1 Pre-processing

Preprocessing is a critical phase in medical image analysis to enhance image quality, reduce noise, and prepare the data for accurate segmentation and feature extraction. In this research, preprocessing is applied to both fundus images and CT lung images using a Gaussian filtering technique.

3.1.1 Gaussian Filtering for Image Denoising

Medical images often contain various types of noise due to acquisition hardware limitations or patient movement. To suppress this noise and preserve structural details, we use a Gaussian filter, a widely adopted linear smoothing filter.

The 2D Gaussian function is defined as:

$$G(x,y) = \frac{1}{2\pi\sigma^2} \cdot \exp\left(-\frac{x^2+y^2}{2\sigma^2}\right) \tag{1}$$

Where, (x, y) are the spatial coordinates of the image, σ is the standard deviation of the Gaussian kernel, controlling the degree of smoothing.

The Gaussian filter is applied via convolution between the input image $I(x, y)$ and the Gaussian kernel $G(x, y)$:

$$I_{smooth}(x,y) = (I * G)(x,y) = \sum_{i=-k}^{k} \sum_{j=-k}^{j} I(x-i, y-j) \cdot G(i,j) \tag{2}$$

Here, $I_{smooth}(x, y)$ is the denoised image, and the summation is taken over the kernel size.

3.1.2 Intensity Normalization

To ensure consistency across image samples and improve the performance of the segmentation and feature extraction steps, intensity normalization can be optionally applied. The normalized pixel intensity I_{norm} is computed as:

$$I_{norm}(x,y) = \frac{I(x,y)-\mu}{\sigma} \tag{3}$$

Where, μ is the mean intensity of the image, σ is the standard deviation.

This standardization ensures that the pixel values have a zero mean and unit variance, which aids in faster convergence during neural network training.

3.2 Segmentation

Segmentation plays a pivotal role in medical image analysis by isolating relevant regions of interest (ROIs), such as pathological tissues or lesions, from background structures. In this research, segmentation is applied to preprocessed fundus and CT lung images to extract the infected or abnormal regions for subsequent feature extraction. The method employed is Fuzzy C-Means (FCM) Clustering, which is well-suited for segmenting complex biomedical images due to its ability to handle image uncertainties and overlapping structures.

3.2.1 Rationale for Fuzzy Clustering

Traditional hard clustering algorithms assign each data point to a single cluster, which is often unsuitable for medical images where boundaries between healthy and diseased tissues are often fuzzy or indistinct. In contrast, Fuzzy C-Means (FCM) assigns each pixel a degree of membership to each cluster, providing more flexible and realistic segmentation. Given an image with N pixels and a desired number of clusters C, the objective of FCM is to minimize the following cost function:

$$J = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^{m} \left\| x_i - c_j \right\|^2 \quad (4)$$

Where, x_i is the i[th] data point, c_j is the centroid of the j[th] cluster, $u_{ij} \in [0,1]$ is the membership degree of x_i in cluster j, $m > 1$, is the fuzzification parameter that controls the degree of fuzziness, $\|x_i - c_j\|$ is the Euclidean distance between the pixel and the cluster center.

3.2.2 Optimization Procedure

The FCM algorithm iteratively updates the cluster centers c_j and the membership degrees u_{ij} using the following update equations:

Centroid update: $$c_j = \frac{\sum_{i=1}^{N} u_{ij}^{m} x_i}{\sum_{i=1}^{N} u_{ij}^{m}} \quad (5)$$

Membership update: $$u_{ij} = \frac{1}{\sum_{k=1}^{C} \left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|} \right)^{\frac{2}{m-1}}} \quad (6)$$

The algorithm stops when the improvement in J is below a predefined threshold $\in$, or after a maximum number of iterations.

3.2.3 FCM in the Proposed Model

In this research, FCM is used to segment the disease-infected regions in:

- Fundus images – to identify vascular leakage, hemorrhages, or exudates related to diabetic retinopathy.
- Lung CT images – to isolate regions with pathological patterns such as emphysema, ground-glass opacities, fibrosis, or micronodules.

Each preprocessed image is reshaped into a 1D vector and subjected to FCM clustering to classify pixels into normal and abnormal tissue types. The resulting segmentation mask highlights the regions with high membership to the disease-related clusters.

3.2.4 Post-Segmentation

To facilitate feature extraction and visualization, the fuzzy membership map can be converted into a binary mask by applying a threshold:

$$S(x,y) = \begin{cases} 1, & \text{if } \max_j(u_{ij}) > T \\ 0, & \text{otherwise} \end{cases} \quad (7)$$

Where $T \in [0.5, 0.8]$ is an empirically chosen threshold. This binary mask serves as the input for texture feature extraction in the next phase of the model.

The FCM offers the advantages of Soft classification, Noise tolerance, and Scalability in Medical Image Segmentation. The final segmented output clearly highlights the infected or abnormal regions in both modalities such as fundus images and lung CT images.

3.3 Feature Extraction

Feature extraction is a vital stage in the image analysis pipeline, transforming raw pixel data into compact, informative representations that can be used for classification. In the proposed model, after preprocessing and segmentation, features are extracted from the identified abnormal regions in both fundus images and CT lung images using the Gray-Level Co-occurrence Matrix (GLCM). GLCM is a statistical texture analysis method that captures spatial relationships between pixels, which are particularly useful in medical imaging where structural patterns reflect pathological changes.

3.3.1 Gray Level Co-occurrence Matrix (GLCM)

GLCM is a statistical method that considers the spatial relationship between pixels. It measures how often a pixel with a specific intensity value i occurs in relation to another pixel with intensity j, separated by a distance d and orientation θ. The GLCM $P(i, j; d, \theta)$ is defined as:

$$P(i, j; d, \theta) = \sum_{x=1}^{M} \sum_{y=1}^{N} \begin{cases} 1 & \text{if} I(x,y)=i \text{ and } I(x+\Delta x, y+\Delta y)=j \\ 0 & \text{otherwise} \end{cases} \quad (8)$$

Where $\Delta x = d \cdot \cos(\theta)$, $\Delta y = d \cdot \sin(\theta)$, and $I(x, y)$ denotes the grayscale intensity at pixel location (x, y).

From the GLCM matrix, the following five statistical features are used in this model:

1) Contrast

Contrast measures the local intensity variation between a pixel and its neighbor over the entire image. It reflects how much the gray levels of pixels differ from each other.

$$\text{Contrast} = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (i - j)^2 \cdot P(i, j) \quad (9)$$

2) Correlation

Correlation measures the linear dependency between the gray levels of neighboring pixels. It reflects how much one-pixel value can be predicted by its neighbor.

$$\text{Correlation} = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} \frac{(i-\mu_i)(j-\mu_j) \cdot P(i,j)}{\sigma_i \cdot \sigma_j} \quad (10)$$

Where, μ_i and μ_j are means of rows and columns. σ_i and σ_j are standard deviations. A value near 1 or -1 indicates strong correlation; near 0 implies no correlation.

3) Energy

Energy measures the uniformity or textural uniformity of an image. It is the sum of squared elements in the GLCM.

$$\text{Energy} = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} P(i, j)^2 \quad (11)$$

High energy values indicate fewer dominant gray-level transitions, meaning a more uniform or homogenous texture.

4) Homogeneity

Homogeneity measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal. It emphasizes the contributions of neighboring pixel pairs with small intensity differences.

$$\text{Homogeneity} = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} \frac{P(i,j)}{1+|i-j|} \quad (12)$$

Higher values of homogeneity indicate less contrast or more similarity between pixels.

3.3.2 Feature Vector Construction

The GLCM features are computed at multiple orientations and distances. The final feature vector $f \in \mathbb{R}^n$ is constructed by concatenating features across these directions:

$$f = [\mathrm{Contrast}_{0^\circ}, \mathrm{Correlation}_{0^\circ}, \mathrm{Energy}_{0^\circ}, \mathrm{Homogeneity}_{135^\circ}] \quad (13)$$

This multidirectional approach ensures rotational invariance and robustness against orientation-based variability.

3.3.3 Feature Normalization

To standardize the range of extracted features before feeding them into the DNN, min-max normalization is applied:

$$f_i^{norm} = \frac{f_i - \min(f)}{\max(f) - \min(f)} \quad (14)$$

This scales all features to the range [0, 1], improving training stability and convergence of the classification model.

3.3.4 Role in Disease Differentiation

Each of the four target lung disease types in diabetic patients exhibits distinct textural characteristics that are captured through these GLCM features:

- **Emphysema** - Reduced contrast and homogeneity due to tissue degradation.
- **Ground Glass Opacity** - High homogeneity, low contrast.
- **Fibrosis** - High contrast and correlation due to fibrotic banding.
- **Micronodules** - High energy and local contrast variation.

By capturing these properties numerically, GLCM features provide a reliable and interpretable representation for classification.

3.4 CLASSIFICATION

The final phase of the proposed diagnostic pipeline involves the classification of lung disease types in diabetic patients based on the features extracted from segmented fundus and CT images. This is achieved using a Deep Neural Network (DNN) model trained on texture-based features derived from the GLCM. The goal of this stage is to classify the input into one of four diabetic lung disease categories.

3.4.1 Deep Neural Network Architecture

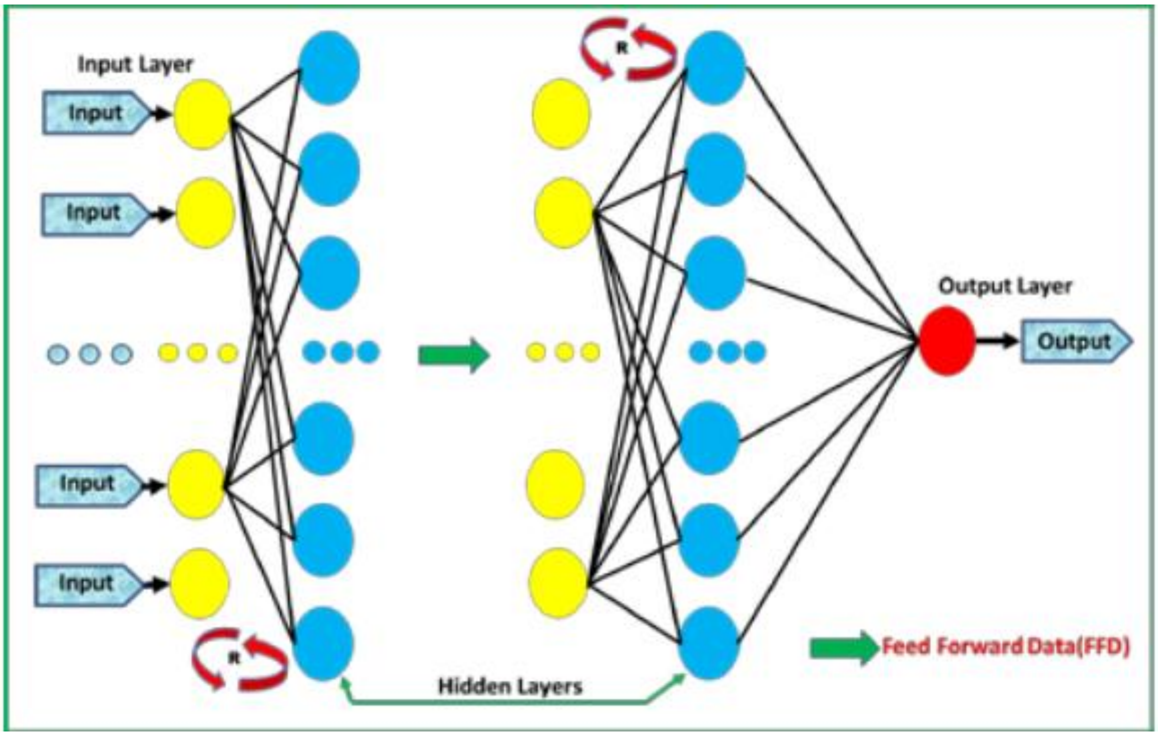


Figure 2. Deep Neural Network Architecture

A typical feed-forward DNN is composed of:

- An input layer receiving the GLCM feature vector.
- One or more hidden layers with nonlinear activation functions.
- An output layer with softmax activation to classify into four categories.

Let the DNN be defined by L layers. The forward pass through the DNN is described as:

Linear Transformation: $z^{(l)} = W^{(l)}a^{(l-1)} + b^{(l)}$ (15)

Activation Function: $a^{(l)} = f(z^{(l)})$ (16)

Where, $a^{(l-1)}$ is the activation from the previous layer, $W^{(l)}$ and $b^{(l)}$ are the weight matrix and bias vector of layer l, $f(\cdot)$ is the activation function.

The final output layer produces a vector $y \in \mathbb{R}^4$, where each element y_i represents the probability of belonging to class i. The softmax function is used:

$$P(y_i|x) = \frac{e^{z_i}}{\sum_{j=1}^{4} e^{z_j}} \quad (17)$$

The class with the highest probability is selected as the final prediction:

$$\hat{y} = \arg\max_i P(y_i|x) \quad (18)$$

3.4.2 Loss Function and Training

The model is trained using the cross-entropy loss function, suitable for multi-class classification:

$$L = -\sum_{i=1}^{4} y_i \log(\hat{y}_i) \quad (19)$$

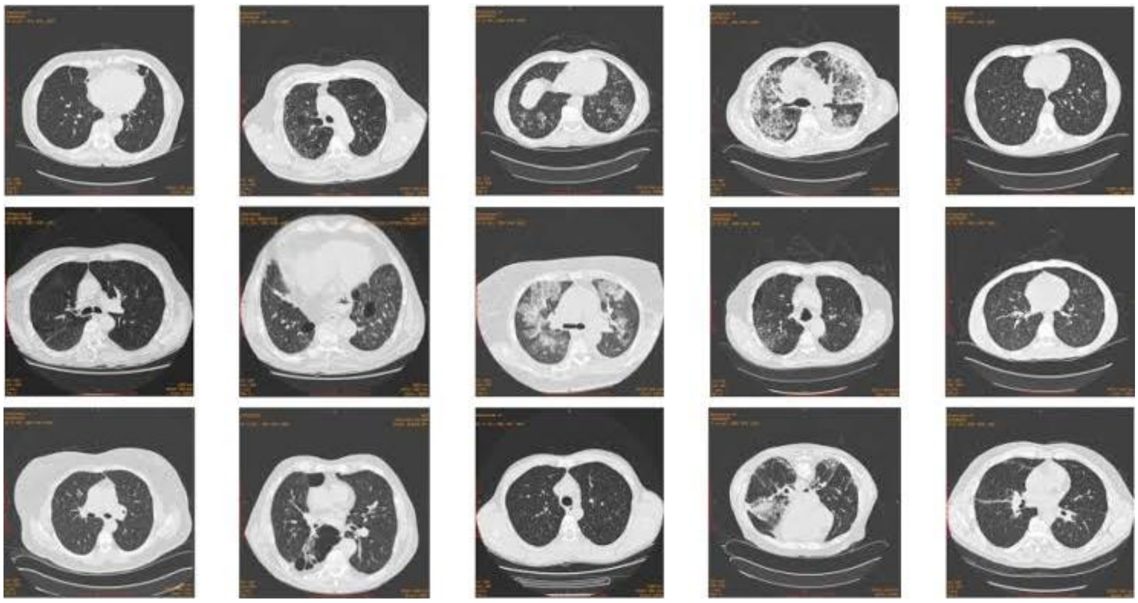
Where, $y_i \in \{0,1\}$is the ground truth label, $\hat{y}_i$ is the predicted probability from the softmax output.
The weights and biases are optimized using backpropagation and stochastic gradient descent (SGD) or its variants.
The gradient updates follow:

$$\theta \leftarrow \theta - \eta \frac{\partial \mathcal{L}}{\partial \theta} \quad (20)$$

Where, θ includes $W^{(l)}$, $b^{(l)}$, and η is the learning rate.

4. RESULTS AND DISCUSSION

The proposed diabetic lung disease classification model demonstrates promising results in accurately detecting and classifying lung abnormalities based on diabetic stages using combined fundus and CT images. The efficiency of the proposed model is evaluated using a publicly available dataset. The sample images shown in figure 3.



(a) Normal Chest (b) Type 1: Emphysema (c) Type 2: Ground Glass (d) Pre-Diabetic: Fibrosis (e) Gestational Diabetic: Micronodules

Figure 3. Sample images of input dataset

Figure 4 illustrates the Graphical User Interface (GUI) developed for predicting the diabetic class associated with the input image. The interface allows users to upload an input image, upon which it sequentially performs preprocessing, segments the region of interest (ROI), extracts texture features using the Gray Level Co-occurrence Matrix (GLCM), and finally classifies the image using the pre-trained Deep Neural Network (DNN) model to display the predicted diabetic lung disease category.

Figure 4. The GUI shows the predicted diabetic type for the given input

Figure 5 presents the accuracy graph for both the training and validation datasets, highlighting the model's learning performance over successive epochs. Figure 6 illustrates the corresponding loss graph, showing the reduction in training and validation loss during the model training process, which indicates the model's convergence and generalization capability.

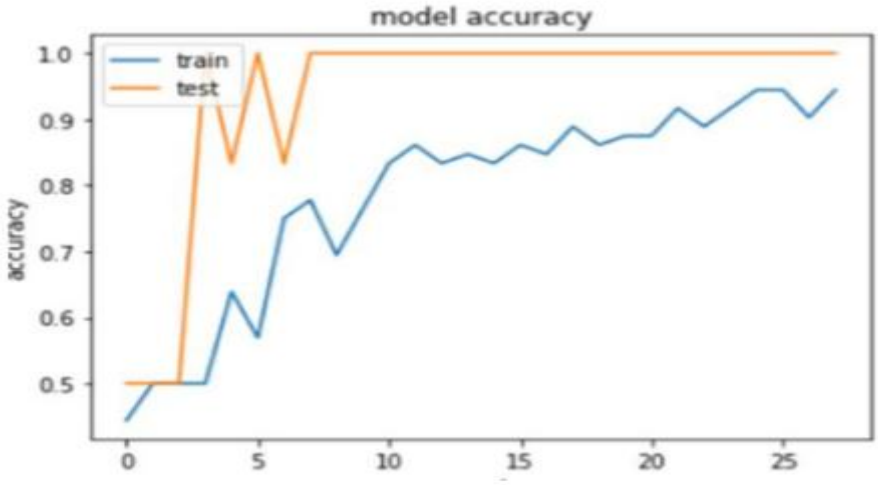


Figure 5. Accuracy graph of Training data and Validation data

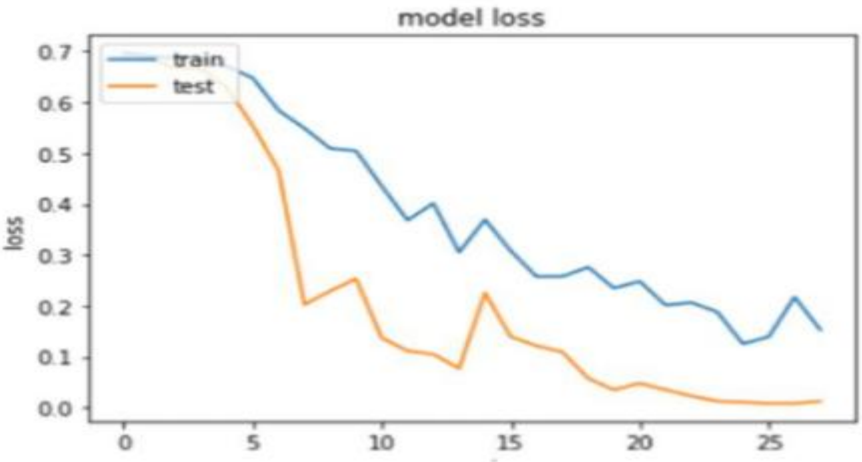


Figure 6. Loss graph of Training data and Validation data

To evaluate the effectiveness of the proposed Deep Neural Network (DNN) classifier for the detection and classification of diabetic-related lung diseases, a comparative analysis was conducted against several widely used conventional machine learning algorithms. These include Support Vector Classifier (SVC), Decision Tree Classifier (DTC), K-Nearest Neighbors (KNN), and Naïve Bayes Classifier (NBC). The performance of each algorithm was assessed in terms of classification accuracy using the same preprocessed and feature-extracted dataset to ensure a fair and consistent evaluation. The results reveal that the DNN classifier significantly outperforms all traditional methods, achieving an impressive accuracy of 94.79%. This superior performance can be attributed to the DNN's ability to model complex non-linear patterns and its capability to learn deep hierarchical features from the input data, which is particularly beneficial for medical images with subtle differences among disease classes.In comparison, the Naïve Bayes classifier, which assumes feature independence, achieved an accuracy of 89.16%, showing decent performance but falling short in capturing inter-feature dependencies. The KNN classifier reached 77.58%, performing moderately well, but its reliance on local neighborhood distances makes it sensitive to noise and less effective in high-dimensional spaces. The Decision Tree classifier, known for its interpretability, achieved 73.41% accuracy but often tends to overfit the training data, reducing generalization. The Support Vector Classifier recorded the lowest accuracy of 68.23%, likely due to its limitations in handling overlapping classes and its reliance on kernel tuning. These findings clearly demonstrate that the proposed DNN-based approach provides a more robust, scalable, and accurate solution for classifying diabetic lung conditions. Its deep architecture, combined with GLCM feature

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extraction and efficient training, enables it to learn subtle differences across complex medical images more effectively than shallow, rule-based models. This comparison strongly supports the suitability of DNN for real-time diagnostic systems and large-scale screening applications in the healthcare domain.

Table 1. Comparison of accuracy with existing approaches

ALGORITHM	ACCURACY (%)
Support vector classifier	68.23
Decision Tree Classifier	73.41
KNN Classifier	77.58
Naïve Baye's Classifier	89.16
DNN Classifier	94.79

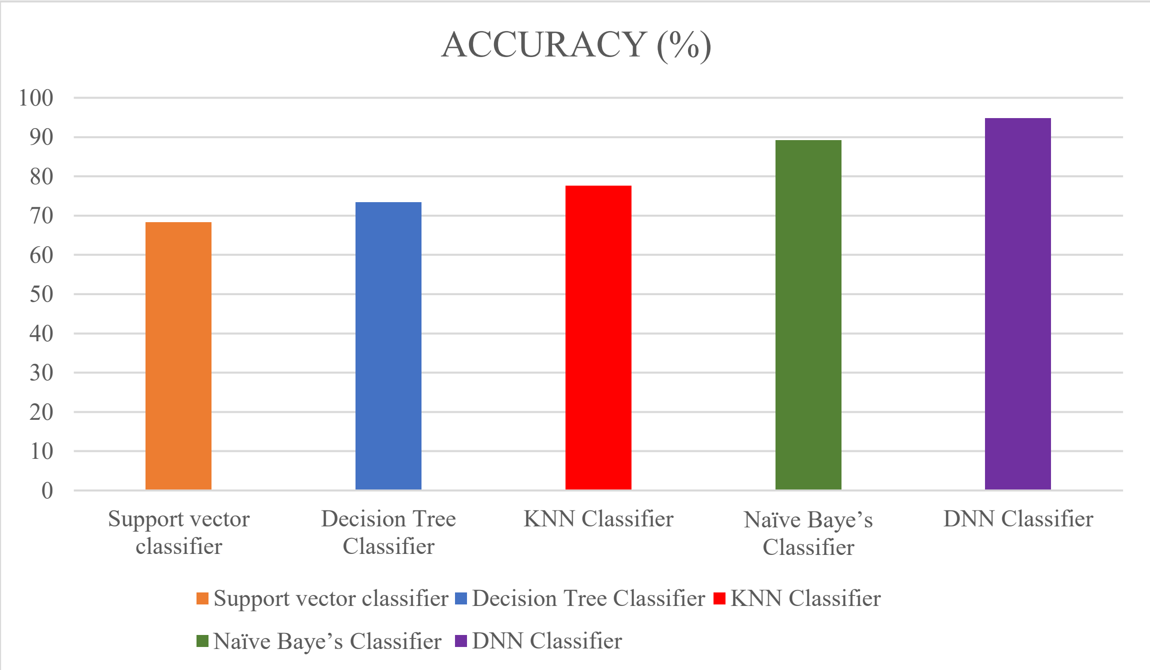

Figure 7. Accuracy comparison with existing techniques

5. CONCLUSION

In this study, a novel Deep Neural Network (DNN)-based classification system was proposed for detecting and diagnosing lung diseases in diabetic patients using a combination of fundus and CT scan images. The preprocessing phase effectively enhanced image quality using Gaussian filtering, followed by precise segmentation of the region of interest through fuzzy clustering. Discriminative texture features were extracted using the Gray Level Co-occurrence Matrix (GLCM), which were then classified using a trained DNN model. The system demonstrated high classification accuracy, particularly in identifying disease types associated with various stages of diabetes, such as emphysema, ground-glass opacity, fibrosis, and micronodules. The experimental results affirm the model's ability to generalize well across diverse patient data and outperform traditional classifiers like SVM, KNN, Decision Tree, and Naïve Bayes.This integrated diagnostic approach not only strengthens early detection efforts for lung complications in diabetic patients but also introduces a cost-effective and scalable solution for clinical deployment. By incorporating fundus imagery alongside CT scans, the model leverages multimodal data to improve diagnostic precision, representing a significant advancement in AI-driven healthcare. Future work may explore extending this framework using transformer-based models, 3D convolutional architectures, or federated learning to preserve data privacy in multi-hospital environments. Overall, the proposed system holds strong potential for mass screening, aiding radiologists and clinicians in timely and accurate diagnosis, ultimately contributing to improved patient outcomes in diabetes-related lung pathology.

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