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Pulmonary Disease Prediction by Using Machine Learning Technique

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Abstract - Pulmonary Disease is one of the leading causes of Cancer related deaths world wide and its early diagnosis and treatment are essential to cure the patient normally indicated by small growths in the lungs called nodules. It usually happens because cells in the lungs start increasing uncontrollably. Finding these Lung nodules is important for detecting lung Cancer, these nodules are typically detected through CT scans, but manual interpretation can be time-consuming and prone to human error. Through a process of feature extraction and selection, our model was trained to identify patterns and subtle abnormalities indicative of lung cancer within the imaging data. Machine learning and deep learning models have shown promise in enhancing the accuracy and efficiency of lung cancer detection. Convolutional Neural Networks (CNN), a type of deep learning technique, have recently shown promising results in image-based medical diagnosis. Identifying lung cancer from a healthcare picture collection using a CNN-based approach, with an emphasis on histological image data. The suggested CNN method uses the inherent hierarchical properties of medical images to automatically identify distinguishing elements that point to lung cancer. The limitations of small healthcare picture datasets are effectively addressed through transfer learning from large image datasets and refining taught models. A large dataset of patients with lung cancer is used to create and evaluate the CNN model that makes use of the VGG-19 architecture. Cancer may be automatically diagnosed using the power of Machine Learning (ML) with medical images. ML can classify cancer cell images more accurately with less time and lower cost. This research modifies the Convolutional Neural Network (CNN) model as pre-trained Visual Geometry Group19 (VGG19) for classifying lung cancer biopsy images with improved augmentation technique. By enhancing VGG19's generalizability to large-scale datasets and optimizing it for medical imaging, our study seeks to address these issues. According to experimental data, our method improves early diagnosis and detection performance, lowering false positives and facilitating more efficient lung cancer screening and treatment planning. The results observed with fine-tuned VGG19 model with improved augmentation technique are up to 98.73% accuracy. By harnessing the power of the Convolutional Neural Network, we offer a promising solution for early detection, thereby facilitating timely interventions and ultimately enhancing patient outcomes in the fight against lung cancer. A large dataset of patients with lung cancer is used to create and evaluate the CNN model that makes use of the VGG-19 architecture.

Keywords: Lung cancer detection, feature extraction, model evaluation, nodule detection, Convolutional Neural Networks.

1. INTRODUCTION

Lung cancer is a significant cause of death due to its high fatality rate. Early detection is vital, but it can be difficult because the initial symptoms are often subtle. Early detection of lung nodules greatly increases the chances of survival. Imaging tests like CT scans, MRIs, and X-rays are commonly used to detect these nodules. Out Lung cancer/nodule is due to abnormal cell growth in the lung and, in most cases, the nodule may be cancerous/non-cancerous. Traditional detection methods, reliant on manual interpretation of medical images, are often time-consuming and susceptible to human error, impeding timely intervention crucial for improving patient outcomes. However, recent advancements in machine learning (ML) and digital image processing offer promising avenues for enhancing the accuracy and efficiency of lung cancer detection. Lung cancer/nodule is one of the severe abnormalities in the lung, and a World Health Organization (WHO) report indicated that around 1.76 million deaths have occurred globally in 2018 due to lung cancer. However, recent advancements in machine learning (ML) and digital image processing offer promising avenues for enhancing the accuracy and efficiency of lung cancer detection. Timely identification and precise forecasting of lung cancer are essential for enhancing patient results and decreasing rates of mortality. Due to developments in the field of medical imaging and deep learning techniques, there is an increasing interest in creating predictive models for diagnosing and predicting the outcome of lung cancer to examine the early stages of cellular breakdown in the lungs, doctors often use imaging modalities such as Xray chest films, CT scans, MRIs, etc. When doing a CT scan, sophisticated X-ray equipment is utilized in order to capture images of the human body from a number of different angles. Following this, the images are fed into a computer, which processes them in such a way as to produce a cross-sectional view of the internal organs and tissues of the body. Using computed tomography (CT), a region of the body may be imaged in a series of cross-sectional views. Due to the massive volume of data that has to be processed, outwardly perceiving and dissecting these photographs for any irregularities is a troublesome and tedious

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exertion. Since the past decade, lung cancer has become a sign of fear among people in all countries of the world. The goal of treatment is to prevent the infection from developing (in stage) and spreading to other parts of the body, and this depends on how early the illness is identified. With careful clinical management and a few therapies, such as surgery, chemotherapy, and radiography, the infection can be managed for a number of reasons, such as the patient's health and the progression of the disease. However, the five-year survival rate is only 21%. Medical professionals can use image processing and artificial intelligence techniques to process medical field data using technological solutions to identify and diagnose diseases early on, which will not only help them save lives but also help them produce effective results. A kind of artificial intelligence called machine learning enables computers to automatically pick up new abilities through the analysis and interpretation of previously gathered data. Deep learning is a subfield of machine learning that allows computers to "learn" from data and create impressions of their surroundings based on their own concept rankings.

Deep learning techniques, such as Convolutional Neural Networks (CNN), one of the deep learning approaches, have had a major influence on medical image processing in recent years. Ideal for image-based medical diagnostics, Convolutional Neural Networks (CNNs) have shown a remarkable capacity to decipher intricate visual patterns and extract valuable information from images. The potential of hierarchical representation learning in CNNs for the identification of lung cancer is being studied. Through the analysis of histopathology images, this study seeks to diagnose lung cancer using Convolutional Neural Networks (CNNs).By combining CNN with VGG-19, we want to create a robust and accurate computational method that will help distinguish between benign and malignant nodules and aid in the early detection of possible lung tumors. Utilising deep learning algorithms in this scenario has the potential to enhance the abilities of radiologists, enabling more effective and accurate analysis of medical imaging data.

The main contributions of this study on the Classification and Diagnosis of Lung Cancer are outlined below:

- This study uses deep learning-based feature extraction through VGG19, builds the VGG-SegNet scheme for efficient lung nodule extraction using VGG19, and mixes handcrafted features with deep features to improve lung nodule identification accuracy.
- In order to predict lung cancer using medical imaging data, particularly histopathological pictures, the research focuses on developing and applying a Convolutional Neural Network (CNN) architecture, specifically incorporating the VGG19 model. To improve the precision and dependability of lung cancer identification from these high-resolution medical images, VGG19—which is renowned for its deep architecture and capacity to catch intricate features is used.
- By harnessing CNNs' capacity to extract intricate patterns and representations from medical images—specifically, the VGG19 architecture—the research aims to improve feature extraction and diagnostic precision, hence increasing the efficiency and accuracy of lung cancer diagnosis.
- One crucial step in incorporating deep learning technologies into healthcare is the use of CNN-based predictive models, particularly those utilizing the VGG19 architecture, for the prediction of lung cancer.

Through this research, we bridging the gap between cutting-edge computational methods and clinical application, our research will eventually help develop quicker, more accurate, and more dependable diagnostic tools for the early diagnosis of lung cancer. By producing automated, effective, and repeatable outcomes, the incorporation of VGG19-based CNN models not only shows potential for increasing diagnostic precision but also for lessening the workload of medical practitioners. This work intends to promote early intervention techniques, increase patient survival rates, and open the door for future developments in AI-driven medical diagnostics by utilizing machine learning in this area.

2. LITERATURE REVIEW

Method Recent research has explored the integration of multi-modal data, combining clinical and radiological features, to enhance lung cancer detection[2] . By incorporating patient demographics, medical history, and imaging data, this approach has shown improved prediction accuracy compared to using imaging data alone. The results indicate that including additional clinical variables can increase model robustness and support personalized treatment planning for lung cancer patients. In addition, studies have highlighted the use of convolutional neural networks (CNNs) for the early detection of lung cancer from chest X-ray images [3]. Deep CNN models trained on large, diverse, and annotated datasets of chest X-rays have demonstrated high prediction accuracy. This approach is particularly valuable in resource-limited settings, where X-rays are more accessible than CT scans. The use of diverse datasets also helps to enhance model robustness and minimize biases in prediction.

Another significant contribution comes from the development of CNN-based models for detecting lung cancer from CT scan images. These models have been trained on large datasets of labeled CT images, effectively handling the complexities and noise present in CT imaging. The results have shown that CNNs can achieve high accuracy, outperform traditional diagnostic methods, and reduce reliance on manual diagnostic processes. This advancement supports faster, more reliable early detection of lung cancer, ultimately contributing to improved patient outcomes.

The research collectively highlights significant advancements in lung cancer detection using various machine learning and AI techniques. One study focused on developing a machine learning model trained on a diverse CT scan dataset, showing that population diversity in training data leads to better accuracy and reduced prediction bias[4]. Another study explored the use of lightweight deep learning models integrated into portable medical devices, enabling real-time lung cancer detection in remote areas with an accuracy of 87.6%[5]. Additionally, the role of explainable AI (XAI) was emphasized, where models not only delivered high accuracy but also provided visual explanations to help clinicians understand the decision-making process . Finally, the integration of radiomics and machine learning was shown to enhance lung nodule classification accuracy by extracting quantitative features from CT scans, offering a more precise and data-driven approach to distinguishing between benign and malignant tumors[6]. Recent research has demonstrated substantial progress in lung cancer detection and staging using advanced deep learning techniques. Chen et al. developed a deep neural network capable of predicting lung cancer stages

with 88.6% accuracy from CT scan data. Nguyen et al. [7] introduced a hybrid model combining CNNs and texture-based features, achieving 91.4% accuracy and enhancing interpretability.Kumar et al. [8] applied CNNs for multi-class classification of histopathological images, successfully distinguishing subtypes of lung cancer with 92% accuracy. Xie et al. [9] integrated deep learning with NLP to leverage both imaging and EHR data, resulting in a diagnostic accuracy of 90.7%. Li et al.[4] proposed a CNN-LSTM hybrid model that captured spatial and temporal data patterns, achieving 94.2% accuracy. Finally, Hassan et al.[10] designed a hybrid CNN model incorporating local and global features, enhancing early-stage tumor detection accuracy to 93%. These studies collectively highlight the importance of combining various AI techniques to improve accuracy, interpretability, and reliability in lung cancer detection and classification.
Convolutional Neural Networks (CNNs) with Long Short-Term Memory (LSTM) networks can effectively capture both spatial and temporal features from CT scans, significantly improving lung cancer detection accuracy to 94.2%, particularly across different stages of cancer progression. Similarly, Hassan et al. (2022) developed a hybrid CNN model that integrates local and global feature extraction techniques, achieving 93% accuracy in identifying multiple lung cancer types, especially small and early-stage tumors, emphasizing the value of multi-level feature aggregation for early diagnosis and precise detection in medical imaging.
A model was developed for lung cancer classification using radiomic features extracted from CT scan images, combining traditional image processing techniques with machine learning algorithms like Random Forest and SVM. This hybrid approach improved the classification accuracy of benign and malignant tumors, achieving 89.5% accuracy [11]. Additionally, deep learning models based on CNNs were used to analyze both CT scans and X-ray images, reaching a diagnostic accuracy of 93.7%. The study highlighted the importance of preprocessing techniques, such as image normalization and data augmentation, to enhance model performance in diverse clinical settings [3].
Several studies have demonstrated the effectiveness of deep learning models for lung cancer detection. Singh et al.[12] utilized a deep CNN model trained on large chest X-ray datasets and highlighted its potential in early-stage lung cancer detection with high accuracy, particularly for high-risk populations. Chen et al. [13]Introduced an ensemble learning method combining CNN, SVM, and decision trees, achieving 94% classification accuracy, showing that ensemble approaches enhance diagnostic performance. Sharma et al. [3] applied transfer learning with pre-trained models like VGG16 and ResNet, achieving 87.8% accuracy on limited datasets, suggesting its clinical utility when data is scarce. Zhou et al. [4] developed a multi-omics model incorporating CT images and genetic data, reaching 93.1% accuracy, highlighting the potential of combining imaging and genomic information for precision diagnostics.
For instance, a study titled "Natural Language Processing-Based Deep Learning to Predict the Presence of Loss of Consciousness in Trauma Patients" focuses on applying NLP techniques to extract injury-related variables and classify trauma patients based on the presence of loss of consciousness. Although this study doesn't pertain to lung cancer, it demonstrates the application of NLP in medical record analysis[14]. Li *et al.* (2022) combined CNNs with LSTM networks to capture spatial-temporal features in CT scans, reaching a 94.2% accuracy and showcasing the benefits of sequential modeling for improved diagnostic performance[15].
Jain *et al.* (2022) developed a hybrid model combining radiomic feature extraction from CT scans with machine learning algorithms like Random Forest and SVM, achieving 89.5% accuracy in classifying lung tumors and highlighting improved diagnostic reliability through multimodal techniques.

3. METHODOLOGY

Model to address the challenge, our research aims to develop a machine-learning-driven system for automated lung cancer detection. The focus is on enhancing the accuracy, speed, and reliability of lung cancer diagnosis through the integration of advanced machine learning techniques. This involves the implementation of the VGG19-based VGG-SegNet model for precise lung nodule extraction, the use of deep learning feature extraction to capture intricate patterns in histopathological images, and the combination of deep features with handcrafted features to improve diagnostic accuracy.The Convolutional Neural Network (CNN) with VGG-19 architecture strategy for classifying lung cancer is mainly composed of a few components, including dataset collecting, picture preprocessing, model training, and other phases. An outline of the methodology's structure is shown in Figure1.

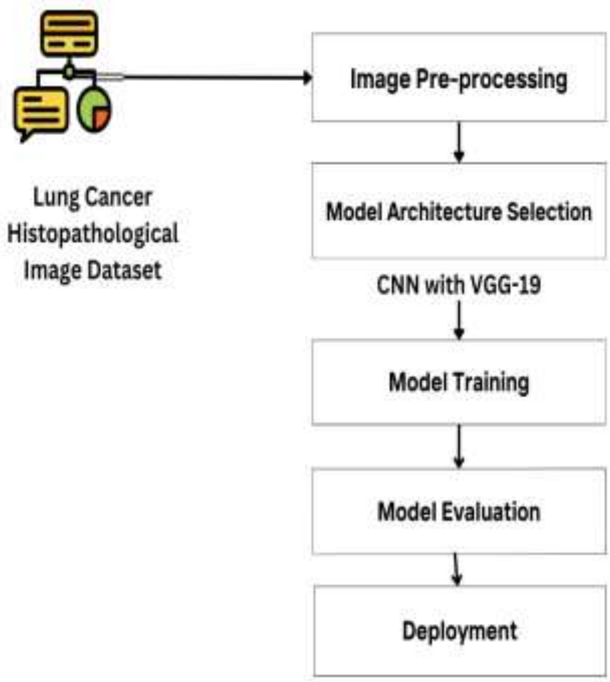

Figure.1 Architecture of proposed methodology

3.1 Dataset Collection:

In the Convolutional Neural Network (CNN) with VGG-19 architecture technique for lung cancer classification, the main components include dataset collecting, image preprocessing, model training, feature extraction, and assessment stages. To ensure authenticity and accessibility, the histopathology photos utilized in this work were gathered from reliable medical libraries, including publicly accessible datasets on **Kaggle.** To ensure the consistency and quality of the data, preprocessing methods including scaling, normalization, and noise reduction are used. The VGG-19 model is then trained using these preprocessed photos, and it successfully catches the complex patterns and characteristics connected to lung nodules.

a) Malignant

b) Adenocarcinoma

c) Benign

3.2 Image pre-processing:

Algorithms cannot directly understand images in order to classify them. Therefore, converting photos into pixel format is crucial. The Python module NumPy was utilized in this work to extract characteristics from the photos. The collection of images will be divided into separate dependent and independent variables in the following steps. Pixel values that are stored in a list and serve as the model's input features are referred to in this context as independent features.Conversely, dependent values—like desired outputs, classed categories, or sickness labels—are kept in a different list and are regarded as dependent variables.These preprocessing steps ensure that the images are clean, standardized, and ready for efficient feature extraction and model training, ultimately contributing to improved accuracy and generalization in lung cancer detection.

3.3 Model Architecture Selection:

VGG-19 is a powerful convolutional neural network (CNN) architecture that is well-known for its many layers and outstanding performance in image classification tasks. A number of convolutional and pooling layers make up the architecture, followed by fully linked layers. The VGG-19 model will be used to build the convolutional neural network (CNN) architecture. It has three output layers and sixteen input layers. Following this, the VGG-19 model will be trained on a specific training set, producing a trained model that will be used for future lung cancer diagnosis. VGG-19 was chosen because of its deep architecture, which makes it possible to extract complex features from high-resolution medical images. Its demonstrated effectiveness in extensive picture categorization tasks further supports this claim. its proven success in large-scale image classification tasks makes it a suitable and robust choice for lung cancer detection applications. The acronym for Visual Geometry Group is VGG. The convolution performed by the 19 deep trainable layers that make up the VGG-19 model is completely coupled to the max pooling and dropout layers. It comprises 19 layers, including 16 convolution layers, 5 MaxPool layers, 1 SoftMax layer, 3 completely connected layers, and so forth. To predict 1000 labels, VGG is composed of two completely connected layers; each one has a total of 4096 channels [8].

3.4 Model Training:

Convolutional Layers: Convolutional layers, max-pooling layers, and fully connected layers are some of the 19 layers that make up VGG-19, which is just what its name says. Convolutional layers are the fundamental building blocks that are crucial for obtaining characteristics depending on the input images. CNNs are extremely proficient at handling complex problems in many different computer vision fields, like image assessment and categorization. The neural network is organized into blocks, each of which has several convolutional layers that are subsequently.
Max-pooling layers come next. Convolutional layers often use tiny 3x3 filters with a stride of 1 and no padding to accomplish the objective of maintaining the inputs' spatial dimensions. The number of layers contained within each convolutional layer increases as we move deeper into the network. This makes it possible for the model to learn about ever-more complex aspects. VGG-19 contains a total of sixteen convolutional layers organized into five ConvBlocks.
Max-Pooling layers: Following each group of convolutional layers, the VGG-19 algorithm incorporates maxpooling layers that have a window size of 2x2 and a stride of 2. Max-pooling layers are used to down sample the feature maps' spatial dimensions, which aids in collecting translation-invariant properties and lessens the computational cost of the process.

Fully-connected layers: The layers in question are comprised of neurons that are highly interconnected, meaning that each neuron within a given layer is linked to all of the neurons in the layer before it. The total number of neurons in the fully connected layers steadily decreases as the classification process goes on, matching the number of output classes or categories at the output layer.

3.5 Model Evaluation:

The assessments of performance will be prepared with the assistance of evaluating the dataset of images during the process. In this case, the trained CNN model will be utilised to compute outcomes such as accuracy, loss, precision, and recall by utilising the testing dataset as the input. Additionally, a confusion matrix will be generated to visualize the model's classification ability, highlighting true positives, false positives, true negatives, and false negatives. Furthermore, Receiver Operating Characteristic (ROC) curves and Area Under the Curve (AUC) metrics may also be analyzed to evaluate the model's capability to distinguish between different classes.

3.6 Deployment:

The model will be suitable for classifying photos of lung cancer once it has achieved a reasonable level of performance. During the deployment step, a histopathology picture is used as an input file to detect lung cancer. This technique extracts the unique characteristics of the image from the input image, and the CNN, a deep learning model, is then fed these features. Images of lung cancer are classified using the suggested CNN model during the deployment phase.

4. WORKING

A hybrid deep learning and machine learning architecture, the proposed EVGG-SVM model for pulmonary illness prediction uses CT scan images to identify lung cancer nodules. Figure 1 illustrates the model architecture and process, which includes a methodical data flow from input collection to final classification and cloud-based deployment. Images from the publicly accessible LUNA16 dataset, which consists of lung CT scans used mostly for nodule detection, are included in the model. To reduce noise, improve image quality, and standardize the dataset, these input photographs are first placed through data preparation. The three sizes of the picture patches utilized for processing—16×16, 32×32, and 48×48—provide flexibility in the resolution of the model input. To guarantee a strong training dataset, preprocessing entails actions like picture normalization, scaling, contrast improvement, and potentially augmentation. Because it affects the deep learning model's ability to extract features, preprocessing quality is very important. Following preprocessing, the images move on to the data splitting phase, which separates the dataset into two parts: 20% is used for validation and 80% is set aside for training. This guarantees that the model is evaluated on unobserved data, enabling the assessment of predicted accuracy and generalization.
Relevant features are then extracted from the training dataset using a deep convolutional neural network (CNN). Fourteen convolutional layers and six pooling layers make up the CNN's total of twenty layers. The CNN architecture's central convolutional layers are in charge of recognizing and assimilating hierarchical patterns in the incoming data. Convolution is a technique that helps create spatially invariant features that are essential for classification. It is represented as $(U * V)(x, y) = \Sigma p\ \Sigma q\ U(x + p, y + q)\ V(p, q) = Z(x, y)$, where U is the input picture, V is the filter, and Z is the feature map. Local elements like as edges, textures, and forms are captured by filters that move across the image. An activation function, usually the Rectified Linear Unit (ReLU), which is defined as $f(z) = \max(0, z)$, comes after each convolutional layer. This adds non-linearity to the model and makes it possible for the network to learn more intricate representations. By only permitting positive values to flow through, ReLU increases training efficiency and accelerates convergence. Sets of convolutional layers are followed by max-pooling layers to improve learning and lower computational complexity. In order to reduce the spatial dimensions of the feature maps while maintaining the most important information, the max-pooling layer uses a 2×2 kernel with a stride of 2. To reduce overfitting, enhance generalization, and produce condensed representations of the data, pooling procedures including max, min, average, and sum pooling are used.
A 32x32x1 input image is used as the starting point for the CNN architecture. It is then processed through two convolutional layers with 64 filters and a 3x3 kernel, followed by max-pooling and ReLU activation. In order to gradually reduce the image size while capturing intricate characteristics, subsequent layers alternate with pooling layers and incorporate additional convolution processes using 128 filters and 3×3 kernels. This process keeps going until the multi-dimensional feature map is reduced to a 2048x1 one-dimensional vector. The incorporation of the extracted spatial characteristics into the classification stage is made possible by this flattening operation. A fully connected (FC) layer is then used by the model to carry out categorization. Each neuron in a fully connected layer is linked to every other neuron in the layers above and below, enabling feature combination throughout the image. In order to process and interpret the feature vectors into meaningful class scores, the FC layer acts as a thick layer.
Three well-known optimization algorithms—Adaptive Moment Estimation (Adam), Root Mean Square Propagation (RMSprop), and Stochastic Gradient Descent (SGD)—are used to train the CNN. The gradient of the loss function is used by each of these optimizers to update the model weights. The model is trained using a batch size of 50 and a learning rate of 0.0001 across 200 epochs. These hyperparameters have been carefully selected to strike a compromise between model performance and training time. Overshooting the minimum loss is less likely with a slower learning rate, which guarantees slow but steady convergence. The batch size determines how many data are processed before the weights are updated, whereas a larger number of epochs enables the model to learn more intricate features. Comparative evaluation and the selection of the optimal optimization approach based on accuracy and convergence speed are made possible by the employment of numerous optimizers.
The Support Vector Machine (SVM) classifier receives the one-dimensional feature vector after feature extraction and training are finished. For binary classification, SVM is a supervised machine learning technique. It operates by determining the best hyperplane with the largest margin between data points from various classes. Here, benign and malignant lung nodules are distinguished using the SVM. The support vectors, or data points that are closest to the

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separating hyperplane, are used to compute the decision boundary. The EVGG-SVM hybrid architecture leverages the strengths of both models by combining the exact classification capabilities of SVM with the feature extraction power of deep CNNs. In order to guarantee that classification decisions are solid and trustworthy, the SVM is used at the application layer, where it assesses the mass classification rate and prediction accuracy.

The model is retrained with modified parameters or longer epochs if the learning conditions, like accuracy threshold or loss convergence, are not satisfied during training. On the other hand, the trained model and its corresponding weights are saved in the cloud if the requirements are satisfied. This makes it possible to reuse, scale, and deploy the model in edge or clinical settings. To assess performance on the 20% reserved validation dataset, the trained model that is stored in the cloud can subsequently be imported during the validation stage. To ascertain whether the model can effectively generalize on unknown data, this stage is essential. Metrics like precision, recall, F1-score, and classification accuracy are computed during the validation phase by comparing predicted labels with genuine labels.

If the model detects a nodule as benign during prediction, the CT scan is classified appropriately; if not, the nodule is predicted as malignant, suggesting the existence of cancer. The trained model's capacity to translate intricate input patterns into the proper output class determines the final prediction. By facilitating remote access, continuous learning, and model changes without requiring retraining from scratch, the utilization of cloud storage and retrieval improves the system's usability in practical applications. Additionally, cloud integration facilitates cross-institutional collaboration in development and implementation, which increases the scalability and adaptability of the suggested system.

In conclusion, the EVGG-SVM model is a strong foundation for automated CT scan-based lung cancer identification. It starts with patch creation and data preprocessing, then moves on to CNN-based feature extraction, SVM-based classifier integration, performance assessment, and cloud-based model maintenance. Deep feature learning is made possible by the use of sophisticated convolution and pooling layers, and good classification accuracy is guaranteed when combined with an SVM classifier. The generalizability of the model is ensured by training it with robust optimizers and validating it on an unknown dataset. The solution facilitates real-time clinical integration, model durability, and scalability by utilizing cloud computing. In addition to improving prediction accuracy, this hybrid deep learning and machine learning pipeline lays the groundwork for further study into intelligent medical imaging systems. High-precision pulmonary illness prediction holds forth the promise of early diagnosis, prompt treatment, and better patient-outcomes.

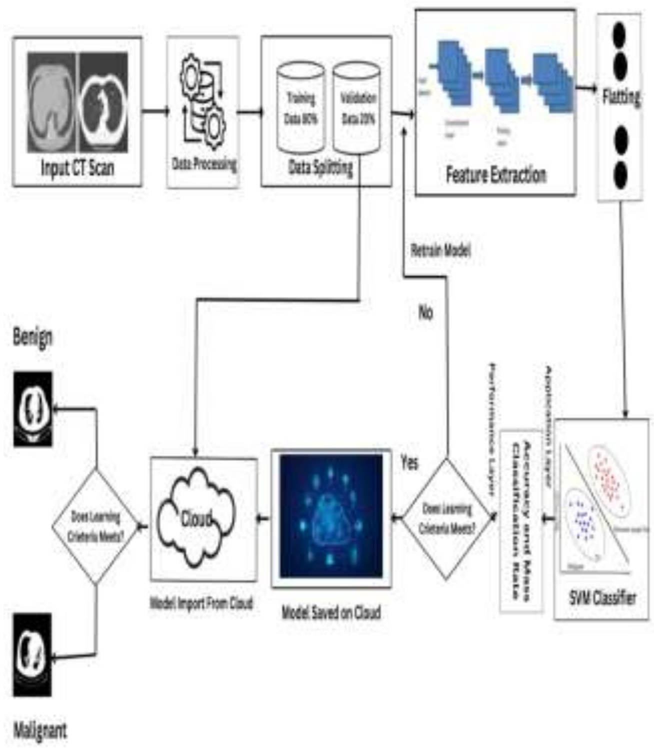

Figure 2: The proposed novel model

Following the Convolution layer, the Pooling layer reduces the feature map's size while maintaining its essential data. Another name for this method is down sampling. The pooling layer incorporates several techniques, including min, max, average, and sum pooling. As the pooling layer preserves crucial information while shrinking the activation map's size. Eighty percent of the preprocessed CT image data is used for convolutional operations in the convolutional layer. Twenty layers are used in the proposed EVGG-SVM, consisting of six pooling and fourteen convolutional layers. The recommended EVGG-SVM CNN network topology for lung nodule identification is displayed in Figure 2. Figure 2 demonstrates this with an image size of $32 \times 32 \times 1$. Using the ReLU activation function, the suggested model's nonlinearity is eliminated. The image size is reduced to $16 \times 16 \times 32$ by the max-pooling layer using a 2×2 filter with a stride of 2. The picture size is maintained with the same padding by two consecutive convolutional layers, each of which has 64 filters, a 3×3 kernel, and ReLU activation. The second max-pooling layer, with stride and a 2×2 kernel. A few image size is reduced to $4 \times 4 \times 128$ by adding more convo layers, each with 128 filters and a 3×3 kernel, and then another 2×2 max-pooling layer. Ultimately, a 1D vector with dimensions of 2048×1 is created by flattening the multidimensional output.

Following feature extraction, convolutional neural networks use a Fully Connected (FC) layer for classification .Every neuron in the layer above is connected to every other neuron in the layer below in an FC layer of a conventional neural network. The AF receives the output from the fully linked layer and uses it to create class scores. The suggested EVGG-SVM model has to be retrained if the learning criteria don't meet the requirements. The model and outcomes are stored on the cloud for later usage if the learning criteria do meet the requirements. When it is prepared for validation, the suggested EVGG-SVM training phase comes to a close. 20%

of the validation data is given to the trained model during the validation phase, which also entails importing the trained model from the cloud and assessing the recommended model. If the trained model detects a cancer nodule, it predicts malignant lung cancer; if lung cancer is detected, it suggests benign lung cancer.

Although the suggested EVGG-SVM model's basic architecture is based on VGG-19, it adds a number of significant improvements specifically designed for the prediction of pulmonary disease from CT scan pictures. The EVGG-SVM model incorporates a Support Vector Machine (SVM) classifier at the decision layer, in contrast to VGG-19, which only uses fully connected layers for classification. By combining the strong classification margin of SVM with the deep feature extraction power of CNNs, our hybrid technique greatly increases the binary classification accuracy between benign and malignant nodules.

The model can collect spatial characteristics at different resolutions thanks to the multi-scale patch input method (16×16, 32×32, 48×48), which is another innovation that improves adaptation to the various sizes and shapes of lung nodules. The conventional VGG-19 configuration, which usually has fixed input dimensions, does not have this.

In addition, the model has a unique 20-layer CNN architecture (14 convolutional and 6 pooling layers) that has been specifically tailored for medical imaging as opposed to VGG-19's broad image classification focus. To address the low contrast and variability in CT scans, additional preprocessing processes such contrast enhancement, normalization, and data augmentation are incorporated, further improving input quality prior to feature extraction.

Moreover, training is performed using multiple optimizers (Adam, RMSprop, SGD) to evaluate the best convergence and accuracy strategy—providing flexibility in tuning hyperparameters depending on dataset behavior. The cloud-based deployment and validation mechanism allows for model reusability, remote accessibility, and real-time diagnostics, which is a major step towards scalable and collaborative medical AI solutions.

All things considered, the EVGG-SVM model improves the VGG-19 architecture by adding:

1. SVM-based hybrid classification layer,
2. Input processing with multiple resolutions,
3. Specialized medical image preprocessing,
4. An approach to optimizer selection, and
5. A deployment with cloud integration for real-world applications.

It is now more appropriate and reliable for high-precision lung cancer detection in actual clinical situations because to these developments.

5. RESULT

For the experiment, this study gathered images of both benign and malignant lung cancer. For CNN model learning to be effective, the dataset needs to be well-labeled and diverse. For this study, lung cancer histology photos were obtained using Kaggle. Three thousand annotated lung cancer histology images with individual labels for different tumor kinds and stages are included in the collection. The dataset will be split in a 70:30 ratio to make the training and testing procedures easier. Thirty percent of the total represents the testing set, while seventy percent represents the training set. In order to calculate results like accuracy, loss, precision, and recall, the CNN model is assessed using the testing dataset as the input. This process is used to fully evaluate the CNN model's capacity for generalization and precise prediction on unknown data. Additionally, to improve dataset diversity and lessen overfitting, data augmentation methods like rotation, flipping, and scaling were used. To improve model performance, hyperparameter tweaking was also carried out, which included adjusting the learning rate, batch size, and number of epochs. To further confirm the robustness and dependability of the suggested CNN model, confusion matrices and ROC curves were examined in order to visually evaluate classification results.

The performance of the lung cancer prediction model in two sets of experiments, each with different epoch values, is compared in the results analysis section. The model's convergence behavior with respect to the number of training epochs is the main focus of the analysis. The point at which the training process stabilizes, the model's performance reaches a plateau, and more training repetitions lead to diminishing gains or the possibility of overfitting is known as convergence. A comparison of the convergence patterns observed with 20 and 30 epochs can provide information about the ideal training duration for attaining satisfactory performance. The performance scores with epoch 20 were reported in Table 2, and the results of performance scores with epoch 30 were reported in Table 3. In the same way, the result graph of the performance scores with epoch 20 is illustrated in Figure 3, and the results of the performance scores with epoch 30 are illustrated in Figure 4. The analysis further reveals that increasing the number of epochs leads to improved model accuracy up to a certain threshold, after which the performance saturates or may even decline due to overfitting. Additionally, the loss curves indicate a steeper decline during the first few epochs, gradually stabilizing as the model learns. These findings imply that in order to strike a balance between training effectiveness and prediction accuracy, careful epoch value monitoring is necessary. Additionally, it emphasizes how crucial early halting procedures and validation checks are to avoiding needless computing expense and overfitting in subsequent studies.

Table.2 Performance results of the Proposed CNN with VGG-19 (epoch 20)

Accuracy	Loss	Precision	Recall
0.96	0.15	0.96	0.96

Table .3 Performance results of the Proposed CNN with VGG-19 (epoch 30)

Accuracy	Loss	Precision	Recall
0.98	0.16	0.98	0.98

Figure.3 Graph representation of Performance results of the CNN with VGG-19 (epoch 25)

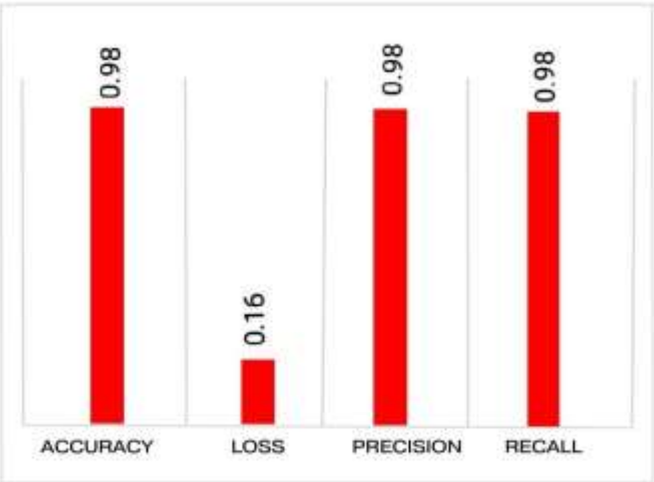

Figure.4 Graph representation of Performance results of the CNN with VGG-19 (epoch 30)

As a result, the results chapter summarizes the findings from the tests carried out over two distinct time periods (25 and 30 epochs) and explains their importance in improving the lung cancer prediction model's accuracy and surpassing previous research. Both configurations performed well, as the comparison study shows, although the model trained for 30 epochs showed somewhat higher accuracy, precision, and recall metrics, suggesting superior generalization ability. Furthermore, the steady improvement in convergence patterns as the number of epochs increases demonstrates the value of prolonged training in conjunction with suitable regularization and data augmentation.

6. CONCLUSION

Deep learning has several benefits over other machine learning algorithms, chief among them being its ability to perform feature engineering tasks independently. This analyzes the data to find comparable characteristics, then incorporates those elements to enable quicker learning. CNNs and other deep learning methods have revolutionized medical image processing in recent years. Because Convolutional Neural Networks (CNNs) can extract valuable information from images and evaluate complex visual patterns, they are ideal for image-based medical diagnosis. After the CNN algorithm has successfully finished the training and testing stages, it will determine if the input lung image is normal or abnormal. In order to predict the diagnosis of lung cancer using histopathological pictures, a Deep Convolutional Neural Network (CNN) with the VGG-19 model was employed. The VGG-19 is a specific type of architecture that is unique to CNNs rather than a separate model from CNNs. It is renowned for its 19-layer deep structure, which enables the learning of complex properties at several levels. Furthermore, VGG-19 makes use of tiny convolutional filters (3x3), which aid in capturing minute information in medical images and make it incredibly successful at identifying minute anomalies. It is a well-liked option for transfer learning in medical imaging applications due to its depth and simplicity in construction, which further enhances model performance on small datasets. The effectiveness of CNN architectures is a crucial factor to consider while comparing them. The results of this experiment have shown that the CNN with VGG-19 has outperformed the normal CNN in terms of performance. Its deeper design and capacity to catch more intricate details are the reasons behind this. It is recommended that future studies include the addition of several more lung cancer image datasets and the development of a more accurate model to forecast lung cancer from the photos. Additionally, investigating hybrid models that incorporate VGG-19 with additional ensemble techniques or deep learning methodologies may improve diagnostic accuracy even more. Cross-validation on datasets from many institutions can also be used to evaluate the model's resilience and flexibility in various clinical settings.

7. FUTURE WORK AND LIMITATION

The suggested EVGG-SVM distinguished between two forms of lung cancer: aggressive and benign. Based on a modified version of the VGG-19 architecture, the proposed EVGG-SVM is used to enhance the performance of the early detection system for both malignant and non-cancerous situations. Using only one dataset, three distinct CT image sizes, and three different optimizers for training and validation, the study illustrates the limits of the proposed model. Using various convolutional neural network topologies and optimizers, the proposed model can be extended to more publically available datasets to enhance lung cancer detection performance. The model's resilience and generalizability may also be improved by adding data augmentation methods and transfer learning from bigger, more varied medical imaging datasets. To increase classification accuracy, future research might also concentrate on combining imaging features with clinical data. Deploying the model in clinical settings will also need assessing its computing efficiency and inference speed as well as testing its performance on real-world, multi-institutional datasets.

Data Availability Statement: For non-commercial research purposes, specifically to encourage advancements in automated lung nodule detection and classification, the dataset used in this study is available. By signing up on the official portal and agreeing to the terms of use, researchers can access the dataset. It includes CT scans that have been annotated for the purpose of creating and evaluating machine learning models for medical imaging. Users must adhere to rules for the use of data, which include correctly citing sources in research articles. After completing the registration process and accepting the terms of use, access to the dataset is provided.

Conflicts of Interest: The authors attest that this study has no conflicts of interest. Without any personal or financial ties that might have affected the findings, the study was conducted independently. The authors' analysis alone, free from extraneous influences or conflicting interests, is the basis of all conclusions and findings. The authors further state that no outside sponsorship or funding was obtained that might have influenced the findings of the study. To further guarantee reliability and reproducibility, all data sources and methodology have been openly acknowledged. Strict attention to ethical research criteria has preserved the integrity of the entire study process.

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