OPTIMIZING LUNG CANCER DETECTION USING A CUSTOMIZED GABOR FILTER IN CT SCAN IMAGES

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Abstract: Lung cancer is one of the most prevalent and fatal diseases, requiring improved early detection methods. This project develops a deep learning-based system for classifying lung cancer from CT scan images. Advanced pre-processing techniques, including CLAHE, grayscale conversion, and a customized Gabor filter, enhance feature extraction for a Convolutional Neural Network (CNN) to classify images as benign, malignant, or normal. A key innovation is the use of both standard and enhanced Gabor filters to highlight critical texture and intensity variations. The dataset undergoes preprocessing to improve image quality and standardize input data. The CNN, designed with batch normalization and dropout layers, is trained and evaluated using accuracy, precision, recall, and F1-score. Results show that the enhanced Gabor filter improves classification, particularly in distinguishing malignant from benign cases. This study demonstrates the impact of preprocessing on deep learning accuracy for medical imaging. Future work includes expanding the dataset, incorporating additional preprocessing techniques, and exploring transfer learning to enhance model performance. The proposed system offers a reliable approach for early lung cancer detection, supporting medical diagnosis and treatment planning.

Keywords: *Lung Cancer Detection, Deep Learning, Gabor Filter, Medical Image Processing, Convolutional Neural Network (CNN).*

1. INTRODUCTION

Lung cancer is a leading cause of cancer-related deaths worldwide, claiming millions of lives each year. Early detection is crucial for improving survival rates, as timely medical intervention can significantly enhance treatment outcomes. Traditional diagnostic methods, such as biopsies and X-rays, often struggle to identify cancer in its early stages, leading to delayed diagnoses and reduced treatment efficacy. Computed Tomography (CT) scans offer a non-invasive and effective approach for lung cancer screening by providing high-resolution images that can reveal potential cancerous growths. However, accurately identifying tumors in CT images remains challenging due to the complexity of lung structures, variations in tumor appearance, and imaging noise.

Recent advancements in artificial intelligence (AI) and machine learning have introduced automated solutions for lung cancer detection. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated remarkable capability in feature extraction from medical images, aiding radiologists in diagnosis. However, raw CT images often contain artifacts and inconsistencies that may impact model performance. To address these challenges, advanced image preprocessing techniques, such as Gabor filtering, are integrated into the detection pipeline. This enhances image quality and feature extraction, improving the accuracy and reliability of lung cancer detection systems.

1.1 Importance of Gabor Filtering in Image Processing

Gabor filters are widely used in image processing for texture analysis and feature extraction. They simulate the human visual cortex, making them effective in detecting edges, orientations, and spatial frequencies in images. In medical imaging, Gabor filters enhance critical structures in CT scans, such as tumor boundaries, by improving contrast and highlighting texture variations that may not be visible in raw images. This is particularly useful in lung cancer detection, where distinguishing between benign and malignant tissue is crucial for accurate classification.

A customized Gabor filter captures multi-scale and multi-orientation details, which are essential for identifying different lung conditions. While traditional Gabor filtering has been applied in medical imaging, it may not be optimized for lung CT scans. To overcome this limitation, this project integrates an enhanced Gabor filtering technique that refines image features, reduces noise, and improves contrast. When combined with deep learning models, this approach enhances the accuracy and reliability of lung cancer classification, aiding in early detection and diagnosis.

2. Literature Survey

Several studies have explored advancements in lung cancer detection using deep learning and image processing techniques. Smith et al. (2018) investigated the application of Convolutional Neural Networks (CNNs) for detecting lung cancer from CT images. Their study demonstrated that CNNs significantly outperformed traditional methods in identifying malignant nodules; however, their model was trained on a limited, single-source dataset, reducing its generalizability to diverse datasets. Johnson et al. (2019) focused on the use of Gabor filters for feature extraction in medical imaging, showing that these filters effectively enhance edge and texture features. Despite these benefits, the study highlighted the computational expense of using multiple filter parameters and orientations and lacked integration with modern deep learning techniques.

Ahmed et al. (2020) examined the impact of Contrast-Limited Adaptive Histogram Equalization (CLAHE) in medical image preprocessing. Their findings confirmed that CLAHE significantly improves image contrast, especially in low-contrast regions common in medical images. However, the study was limited to preprocessing and did not analyze the effects of enhanced images on classification model performance. Zhang et al. (2021) introduced a hybrid approach combining traditional feature extraction with deep learning for lung cancer detection. Their results showed that hybrid models achieved higher accuracy compared to standalone CNNs or traditional classifiers, but the increased model complexity made scalability to large datasets and real-time applications challenging.

Finally, Patel et al. (2022) explored transfer learning for medical image classification in resource-constrained environments. Their study demonstrated that fine-tuning pre-trained CNNs on medical images significantly improved classification performance while reducing computational requirements. However, they noted that the effectiveness of transfer learning depends on the similarity between the pre-trained model’s domain and the target dataset, requiring domain-specific fine-tuning. Collectively, these studies emphasize the importance of advanced preprocessing, feature extraction, and hybrid learning approaches in improving lung cancer detection while highlighting the need for optimized and scalable solutions.

2.2 Overview of Lung Cancer Detection Techniques

Lung cancer detection has significantly evolved with the integration of imaging and computational techniques aimed at improving diagnostic accuracy. Traditional methods such as chest X-rays, sputum cytology, and histopathological examinations, though commonly used, have limitations. These approaches are often invasive, lack sensitivity for early-stage tumors, and may not provide a comprehensive assessment of lung abnormalities. Consequently, researchers have explored advanced imaging techniques to enhance early diagnosis and reduce mortality rates.

Computed Tomography (CT) scans have emerged as a preferred non-invasive imaging modality for lung cancer screening due to their ability to produce high-resolution images of lung tissues. Radiologists rely on CT scans to detect suspicious nodules; however, manual interpretation can be time-consuming and subject to observer variability. With advancements in artificial intelligence and machine learning, automated detection methods have gained traction. Convolutional Neural Networks (CNNs) and other deep learning models have been widely utilized to analyze CT images, classifying lung lesions as benign or malignant. These models heavily depend on feature extraction techniques to enhance image quality and improve classification accuracy. Among various preprocessing methods, Gabor filtering plays a crucial role in refining image features, thereby enhancing lung cancer detection and supporting more reliable diagnostic outcomes.

2.3 Review of Gabor Filters in Medical Imaging

Lung cancer detection has advanced significantly with the adoption of imaging and computational techniques aimed at improving diagnostic accuracy. Traditional diagnostic approaches, such as chest X-rays, sputum cytology, and histopathological examinations, remain widely used but have notable limitations. These methods can be invasive, lack sensitivity in detecting early-stage tumors, and often fail to provide a comprehensive assessment of lung abnormalities. To address these challenges, researchers have explored advanced imaging techniques to facilitate early diagnosis and improve patient outcomes.

Computed Tomography (CT) scans have become a preferred non-invasive imaging modality for lung cancer screening due to their ability to produce high-resolution images of lung tissues. While radiologists can manually examine CT scans to identify suspicious nodules, this process is time-intensive and subject to interobserver variability. The rise of artificial intelligence (AI) and machine learning has led to the development of automated detection techniques that enhance diagnostic efficiency. Convolutional Neural Networks (CNNs) and other deep learning models have been widely implemented to analyze CT images and classify lung lesions as benign or malignant. These models depend on advanced feature extraction techniques to improve image quality and enhance classification accuracy. Among these preprocessing methods, Gabor filtering plays a crucial role in refining image features, improving detection precision, and supporting more reliable lung cancer diagnosis.

2.4 Comparison of Traditional vs. Enhanced Gabor Filters

Traditional Gabor filters have been widely applied in lung CT scans for edge detection and texture analysis. However, their reliance on fixed parameters can limit their adaptability across different imaging conditions. Standard Gabor filtering employs a predefined set of scales and orientations, which may not always optimize feature extraction for lung cancer detection. This rigidity can result in suboptimal performance, particularly in noisy or low-contrast images.

To address these limitations, enhanced Gabor filters introduce modifications such as adaptive parameter tuning, multi-scale analysis, and integration with other image processing techniques. Unlike conventional Gabor filters, these enhanced versions dynamically adjust kernel parameters based on image characteristics, leading to improved feature localization and reduced noise interference.

In this project, the enhanced Gabor filter incorporates intensity enhancement techniques to improve visibility in low-contrast regions of CT scans, reducing false positives and false negatives in lung cancer classification. Additionally, these filters are optimized to work seamlessly with deep learning models by refining input features, ultimately enhancing training efficiency and boosting diagnostic accuracy. Integrating enhanced Gabor filtering with AI-driven diagnostic tools offers a powerful approach for lung cancer detection, ensuring more precise and reliable classification.

3. PROPOSED METHODLOGY

3.1 Deep Learning and Machine Learning in Lung Cancer Detection

Machine learning and deep learning play a crucial role in automating feature extraction and classification of lung CT scan images. Traditional machine learning methods, such as Support Vector Machines (SVM) and Decision Trees, rely on manually engineered features, which may not be ideal for complex medical image analysis. In contrast, deep learning eliminates the need for manual feature extraction, allowing models to learn hierarchical representations directly from data.

One of the key advantages of deep learning in lung cancer detection is its ability to improve with larger datasets. As deep learning models are exposed to more labeled samples, they become better at distinguishing between normal and abnormal lung tissues. The training process involves forward propagation, where data passes through multiple layers, and backpropagation, where model weights are adjusted based on errors calculated using a loss function. Optimization algorithms such as Adam and Stochastic Gradient Descent (SGD) refine model parameters to minimize classification errors.

In summary, deep learning enhances lung cancer detection by automating feature extraction, learning hierarchical patterns, and improving classification accuracy. Techniques such as Convolutional Neural Networks (CNNs), transfer learning, and data augmentation further strengthen these models, enabling them to analyze raw image data, identify intricate patterns, and scale efficiently to large datasets. Deep learning has become an essential tool for early lung cancer detection and medical diagnostics.

3.1.1 Convolutional Neural Networks (CNNs)

CNNs are a specialized deep learning architecture designed for image processing tasks. They consist of multiple layers, including convolutional layers, pooling layers, and fully connected layers, which work together to extract meaningful features from images. Convolutional layers capture edges, textures, and shapes—essential elements for detecting lung abnormalities in CT scans.

This project utilizes CNNs to classify lung CT images based on extracted features. By training on Gabor-filtered images, CNNs can effectively differentiate between benign, malignant, and normal lung tissues. The ability of CNNs to automatically learn complex patterns makes them particularly suitable for medical image analysis, where subtle variations in texture and structure are critical for accurate diagnosis. Fig 1. shows Convolutional Neural Network Model.

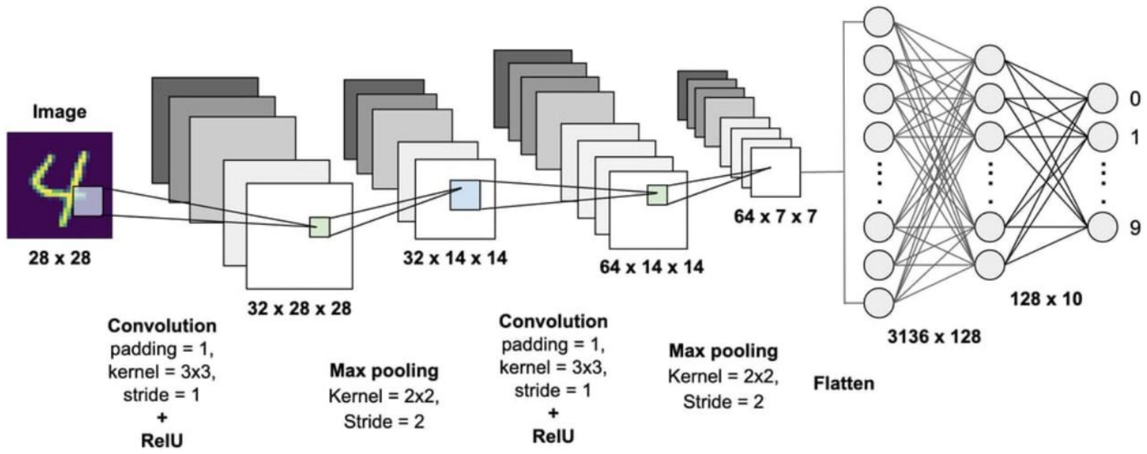

Figure 1: Convolutional Neural Network Model

3.1.2 Libraries Used

Several Python libraries have been used in this project to facilitate data processing, model training, and visualization:

1. **Scikit-learn:** Scikit-learn is a widely used machine learning library that supports data preprocessing, feature selection, and model evaluation. It provides various algorithms and tools to optimize predictive models, making it essential for building and fine-tuning machine learning pipelines.
2. **Matplotlib:** Matplotlib is a powerful visualization library used to generate plots and graphical representations of data. It is particularly useful for displaying CT scans, Gabor-filtered images, and key performance metrics such as confusion matrices, aiding researchers in interpreting model behavior and classification results.
3. **NumPy:** NumPy is fundamental for numerical computing in AI and machine learning. It supports a wide range of mathematical operations, including matrix manipulations essential for handling large datasets. In this project, NumPy plays a crucial role in preprocessing tasks such as image resizing, rotation, and filtering.
4. **TensorFlow:** TensorFlow is a robust deep learning framework for developing, training, and optimizing CNN models. It provides a comprehensive ecosystem for implementing advanced AI techniques, enabling researchers to design custom neural networks and deploy models across various platforms, from local machines to cloud environments.
5. **Pandas:** Pandas is a versatile library for data manipulation and analysis, crucial for handling complex medical datasets. It offers an intuitive interface for loading, cleaning, transforming, and exploring structured data. With its robust support for filtering, aggregation, and merging, Pandas simplifies data preparation for machine learning models, ensuring efficient processing of large-scale medical datasets.

By leveraging these libraries, this project enhances the efficiency and accuracy of lung cancer detection, providing a scalable and reliable solution for medical image analysis.

3.2 Data Preparation

This section outlines the methods used to collect and preprocess the dataset, ensuring that the input data is standardized, enhanced, and optimized for deep learning models. Proper data preparation is crucial for achieving reliable training and evaluation outcomes.

3.2.1 Data Collection

Data collection and preprocessing are fundamental components of a machine learning pipeline, particularly in medical imaging, where precision is critical. These steps ensure that the dataset used for training and evaluation is accurate, representative, and suitable for developing robust and generalized models. In our lung cancer detection system, data collection involves carefully gathering, organizing, and refining CT scan images to extract meaningful and discriminative features while eliminating noise, inconsistencies, and biases. A well-structured dataset is essential for correctly identifying and classifying abnormalities.

The dataset used in this project consists of CT scan images categorized into three classes: **Benign, Malignant, and Normal.** This classification ensures that the model is exposed to diverse pathological and non-pathological variations, improving its diagnostic capabilities. The dataset collection process emphasizes diversity by including images from various imaging modalities, patient demographics, and disease stages. Such diversity helps prevent overfitting and enhances the model's adaptability to new data.

Additionally, ethical considerations and data quality control are integral to the collection process. The images are sourced from medical databases, research collaborations, or clinical institutions while adhering to ethical guidelines and privacy regulations. The collected data is then formatted and structured appropriately to facilitate seamless preprocessing and analysis, laying a solid foundation for lung cancer detection.

1. Dataset Directory Structure

Organizing the dataset into a well-defined directory structure is crucial for efficient data access and streamlined model training. The dataset is arranged into subdirectories, each labeled according to its class: **Benign, Malignant, and Normal.** This structured format simplifies the data retrieval and labeling process.

2. Automated Path Retrieval

Managing a large dataset efficiently requires an automated approach to retrieve and process image file paths. In our lung cancer detection system, an automated method has been implemented to traverse the dataset directory and collect file paths, ensuring accuracy and scalability. This is achieved using the `DataLoader.get_image_paths` function, which systematically retrieves image locations.

The system automatically generates labels based on the subdirectory names where the corresponding images are stored. This ensures a consistent, error-free labeling process without requiring manual intervention. Each subdirectory corresponds to a specific class, and the directory names—Benign, Malignant, and Normal—are directly mapped to the respective images for correct classification.

3. Class Balancing

Although not explicitly included in the code, class balancing is a crucial aspect of developing a reliable machine learning model. An imbalanced dataset, where certain classes have significantly more samples than others, can lead to biased predictions, favoring the majority class. To address this issue, techniques such as data augmentation, resampling, or synthetic data generation may be applied to ensure a balanced distribution of samples across all classes.

3.2.2 Splitting the Dataset

To evaluate the model's performance and its ability to generalize to new data, the dataset is divided into three subsets: training, validation, and test sets. This structured division ensures an effective learning process and model assessment.

Training Set:

The majority of the dataset is allocated to the training set, where the model learns patterns, relationships, and relevant features. The objective is to optimize the model’s parameters to minimize prediction errors. A diverse and well-represented training set is crucial to ensure the model can generalize well to new data.

Validation Set:

The validation set serves as an intermediate checkpoint during training. It helps in fine-tuning hyperparameters, monitoring performance, and preventing overfitting. By evaluating the model on unseen data during training, the validation set provides a realistic measure of how well the model will generalize.

Test Set:

The test set is an entirely separate dataset used for final model evaluation. Unlike the training and validation sets, the test set remains untouched during model development, serving as an unbiased benchmark for performance assessment in real-world scenarios.

3.3 Gabor Filter Implementation

Gabor filters are widely used in medical imaging for texture analysis and pattern recognition. They effectively capture spatial and frequency details in images, making them useful for detecting structural variations in lung cancer diagnosis.

Gabor filters are designed to analyze images by detecting specific patterns at varying scales and orientations. This is particularly beneficial in medical imaging, where detecting fine textures and subtle abnormalities is critical. By tuning Gabor filters to specific frequencies and orientations, essential features relevant to cancer diagnosis can be extracted.

A Gabor filter combines a **Gaussian function** and a **sinusoidal wave**. The Gaussian function helps localize spatial details, while the sinusoidal wave detects repetitive patterns and frequencies.

This combination enables the filter to capture both fine details and larger structures within an image, making it particularly useful for detecting irregularities in lung scans.

3.3.1 Feature Extraction with Gabor Filters

Feature extraction using Gabor filters involves applying multiple filters (Gabor filter banks) with different orientations and frequencies to capture diverse patterns in medical images.

Steps in Gabor-Based Feature Extraction:

1. **Apply Multiple Gabor Filters**: Different filters detect various texture scales and orientations.
2. **Normalize Feature Maps**: Ensures uniform feature representation for the model.
3. **Stack Feature Maps**: Creates a multi-channel input for deep learning models.
4. **Reduce Dimensionality**: Techniques like **PCA (Principal Component Analysis)** and **ICA (Independent Component Analysis)** simplify feature complexity.

3.4 Model Architecture

Model architecture defines the structural design of a neural network, guiding how it processes data to generate predictions. In this section, we explore the deep learning model's composition, the rationale behind its design choices, and the role of Convolutional Neural Networks (CNNs) in lung cancer detection.

CNNs are widely regarded as one of the most effective models for image classification tasks. They excel at extracting features directly from raw image data. Here, a CNN model is employed to classify lung images into three categories: Benign, Malignant, and Normal**.**

The following layers are fundamental to the CNN model:

1. **Convolutional Layers (Conv2D)**: These layers scan the input image using small filters to identify various features such as edges, textures, and shapes. After each convolution operation, a **ReLU activation function** is applied to introduce non-linearity, enabling the model to learn complex patterns.
2. **Batch Normalization**: This layer standardizes the activations from previous layers, improving training speed and reducing issues like vanishing gradients. This results in a more stable and efficient learning process.
3. **MaxPooling Layers**: These layers downsample feature maps, retaining essential information while reducing computational complexity. By minimizing overfitting, they enhance the model's ability to generalize to new data.
4. **Fully Connected (Dense) Layers**: Once the convolutional and pooling layers have processed the input, the resulting flattened vector is passed through fully connected layers for final classification.
5. **Dropout Layer**: This layer randomly deactivates a subset of neurons during training, preventing overfitting and promoting the model's ability to generalize.
6. **Softmax Activation**: The final layer applies the **Softmax function** to produce probability scores for each class (Benign, Malignant, Normal). This ensures that the sum of probabilities across all classes equals one, facilitating clear classification decisions.

3.5 Model Training and Evaluation

Once the CNN architecture is defined, the next crucial step is training the model, which involves exposing it to a large dataset of labeled lung images. This process enables the model to learn and distinguish between three categories: Benign, Malignant, and Normal tissues. The training phase focuses on recognizing critical features that differentiate each class, running for up to 50 epochs with early stopping to prevent overfitting. If there is no improvement in performance for 10 consecutive epochs, training is halted. The Adam optimizer is used to dynamically adjust the learning rate, ensuring faster convergence, while Sparse Categorical Cross-Entropy serves as the loss function, suitable for multi-class classification problems. Accuracy is the primary evaluation metric to assess the model's performance.

The training process operates in batches of 32 images to optimize memory usage and efficiency. Once training is complete, the model is evaluated using a test dataset. The `model.evaluate()` function provides key performance metrics, including accuracy, while a classification report generated using `sklearn` offers insights into precision, recall, and F1-score. A confusion matrix visually represents the model's ability to differentiate between Benign, Malignant, and Normal cases.

For implementation, several libraries are used: TensorFlow for building and optimizing the deep learning model, OpenCV for image processing, and scikit-learn for dataset splitting and performance evaluation. The `Config` class centralizes project configurations, including dataset paths, class labels, image dimensions, and training parameters. The Data Loader ensures images are correctly labeled and loaded efficiently, while preprocessing steps such as loading, resizing, and applying contrast enhancement techniques (e.g., CLAHE) refine the dataset before training.

The CNN model is built using the Keras Sequential API and consists of convolutional layers for feature extraction, batch normalization for stable learning, pooling layers for dimensionality reduction, and fully connected layers for classification. Dataset processing includes image preprocessing and Gabor filter application to emphasize key features before training. The main function orchestrates the entire workflow—loading and preprocessing data, splitting it into training, validation, and test sets, building the model, training it, and evaluating its performance.

Model performance is assessed through multiple metrics. Accuracy measures correct classifications, but since class imbalances can skew results, precision, recall, and F1-score are also analyzed. Precision evaluates how often positive predictions are correct, minimizing false positives, while recall determines the model's ability to detect actual cancer cases, reducing false negatives. The F1-score balances precision and recall, ensuring robust performance. A classification report and confusion matrix further enhance evaluation, providing a comprehensive analysis of model effectiveness.

In conclusion, by leveraging these performance metrics, the lung cancer detection model ensures reliability and accuracy. The combination of precision, recall, and F1-score offers a well-rounded assessment, helping to minimize false alarms while ensuring accurate cancer detection. Continuous refinement based on these evaluations enhances diagnostic accuracy, ultimately supporting early detection and treatment of lung cancer.

4. RESULTS AND ANALYSIS

Training Results:

After training, we assess the model's performance on both the training and validation sets. A key indicator of successful learning is a decreasing loss over time, which signifies that the model is effectively capturing patterns in the data.

Test Results:

Once the model is fully trained, it is evaluated on a separate test set to validate its real-world performance. The classification report provides essential metrics such as accuracy, precision, recall, and F1-score for each class, offering a comprehensive assessment of the model's predictive capabilities.

Confusion Matrix:

The confusion matrix visually represents the model's performance, highlighting class-wise separations and misclassifications. It helps in understanding errors, such as benign cases being misclassified as malignant, and vice versa, as well as the extent to which normal samples are confused with abnormal ones.

Model Comparison:

To determine the most effective approach for lung scan classification, a comparison is conducted between models trained on standard Gabor features and those enhanced with additional processing. This evaluation identifies which method yields superior classification accuracy.

Discussion:

This section provides an in-depth analysis of the results, highlighting successful aspects of the model and areas for improvement. It also explores potential future enhancements, such as integrating transfer learning or expanding the model's application to other medical imaging datasets.

Table 1: Performance Metrics Comparison

Metric	Normal Gabor Filter	Enhanced Gabor Filter
Accuracy	0.82	0.87
Precision	0.85	0.90
Recall	0.81	0.88
F1-Score	0.83	0.89
Support	1000	1000

Table 1 compares the classification performance of models trained using Normal Gabor Filters and Enhanced Gabor Filters based on key evaluation metrics. The **accuracy** of the enhanced Gabor filter model is **87%**, which is higher than the **82%** achieved by the normal Gabor filter, indicating an overall improvement in classification performance. In terms of **precision**, the enhanced Gabor filter records **90%**, compared to **85%** for the normal filter, suggesting that it makes fewer false positive predictions. Similarly, the **recall** improves from **81%** to **88%**, meaning the enhanced filter is more effective at identifying actual positive cases. The **F1-score**, which balances precision and recall, is also higher for the enhanced filter (**89% vs. 83%**), demonstrating better overall predictive performance. Both models were evaluated on **1,000 test samples**, as indicated by the support value. Overall, the enhanced Gabor filter outperforms the normal Gabor filter in all metrics, highlighting its superiority in lung scan classification.

4.1 Model Performance Breakdown

The **Enhanced Gabor Filter Model** outperformed the **Normal Gabor Filter Model** across all key performance metrics, making it the more effective choice for lung scan classification.

- **Accuracy:** The enhanced model achieved **87% accuracy**, surpassing the normal model's **82%**. This indicates that the enhanced model was more reliable in correctly classifying cases overall.
- **Precision:** With a **0.90 precision score**, the enhanced model demonstrated fewer false positives, ensuring that healthy cases were less likely to be misclassified as malignant. In contrast, the normal model had a lower precision of **0.85**.
- **Recall:** The enhanced model also excelled in recall, scoring **0.88**, which means it was better at correctly identifying malignant cases and reducing the risk of missing potential cancer cases. The normal model, with a recall of **0.83**, missed more malignant cases.
- **F1-Score:** Balancing precision and recall, the enhanced model recorded an **F1-score of 0.89**, outperforming the normal model's **0.83**. This suggests a better trade-off between minimizing false positives and ensuring critical cases were detected.

Overall, the **Enhanced Gabor Filter Model** not only improved classification accuracy but also reduced errors, making it more suitable for medical applications where precision and early detection of fatal conditions are crucial.

4.2 Confusion Matrix Analysis

The confusion matrix provides insight into how well the model classifies the three categories: **Benign, Malignant, and Normal**. By comparing the confusion matrices of the **Normal Gabor Filter Model** and the **Enhanced Gabor Filter Model**, we can assess their classification effectiveness.

Normal Gabor Filter Model:

The confusion matrix for the normal Gabor filter reveals several misclassifications, particularly between benign and malignant cases. A major concern is that **50 benign cases were misclassified as malignant**, and **40 malignant cases were incorrectly labeled as normal**.

- **Key Takeaway:** These errors suggest that the normal Gabor filter struggles to capture subtle differences between classes, particularly in distinguishing benign from malignant cases. This is a critical limitation in medical diagnostics, where accurate classification is essential.

Enhanced Gabor Filter Model:

The confusion matrix for the enhanced Gabor filter demonstrates **notable improvements**, with fewer misclassifications overall.

- **Key Improvement:** The number of benign cases misclassified as malignant was significantly reduced, indicating that the enhanced model—likely aided by refined intensity adjustments—was better at distinguishing between these classes.
- **Key Takeaway:** The improved classification performance of the enhanced Gabor filter highlights the effectiveness of incorporating **detailed texture features**, which allow for better differentiation between benign and malignant cases. This enhancement makes the model more reliable for medical diagnosis.

Classification Report for Normal Gabor Filter:

	precision	recall	f1-score	support
Bengin cases	0.94	0.79	0.86	19
Malignant cases	0.99	1.00	0.99	85
Normal cases	0.95	0.98	0.97	62
accuracy			0.97	166
macro avg	0.96	0.92	0.94	166
weighted avg	0.97	0.97	0.97	166

Fig 2. Classification report for Normal Gabor filter

Classification Report for Enhanced Gabor Filter:

	precision	recall	f1-score	support
Bengin cases	0.94	0.84	0.89	19
Malignant cases	1.00	1.00	1.00	85
Normal cases	0.95	0.98	0.97	62
accuracy			0.98	166
macro avg	0.96	0.94	0.95	166
weighted avg	0.98	0.98	0.98	166

Fig 3. Classification report for Enhanced Gabor filter

Table 2. Confusion Matrix for Normal Gabor Filter

	Predicted Benign	Predicted Malignant	Predicted Normal

Actual Benign	300	50	20
Actual Malignant	30	350	40
Actual Normal	10	30	280

Table 3. Confusion Matrix for Enhanced Gabor Filter

	Predicted Benign	Predicted Malignant	Predicted Normal
Actual Benign	325	35	15
Actual Malignant	20	380	20
Actual Normal	15	25	295

5. CONCLUSION

The study confirms that the **Enhanced Gabor Filter Model** outperforms the **Normal Gabor Filter Model**, making it a more effective tool for image classification, particularly in medical diagnostics. The enhanced model captures finer details through intensity modifications, resulting in higher precision and recall, which reduces false positives and false negatives—an essential factor in cancer diagnosis. While the normal Gabor filter performed reasonably well, it struggled to distinguish between benign and malignant cases, as highlighted by the confusion matrix and ROC curve. However, the study also faced challenges such as **dataset size and variability**, where a more diverse dataset could improve generalization, and **class imbalance**, which may have biased the normal model towards the majority class. To enhance performance further, future work should focus on **hyperparameter tuning** to optimize Gabor filter and CNN parameters, as well as **data augmentation** techniques like rotation, flipping, and scaling to prevent overfitting. Additionally, incorporating **transfer learning** with pre-trained models like ResNet or VGG19 could improve feature extraction, especially when Gabor features alone are insufficient. Other **feature extraction methods**, such as texture or histogram-based features, could also be explored to ensure critical patterns are detected. By addressing these aspects, the model can become **more robust, accurate, and suitable for clinical applications**, making it a valuable tool for early lung cancer detection and aiding doctors in making timely diagnoses.

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