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Research Article

Image Enhancement Technique Based on Deep Learning and Hybrid Particle Swarm Optimization for Lung Tumor Classification

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ABSTRACT

Lung cancer is one of the leading causes of death in the modern world. The survival rate is low due to the difficulties in detecting lung cancer in its later stages, when symptoms are present. Consequently, it is essential to recognize issues early. Cancer detection research throughout the whole body is a formidable challenge. Detecting lung cancers is a top priority. Here, computed tomography (CT) images are considered for the identification of lung cancers; other screening procedures include X-ray, CT, and sputum cytology. Computed tomography has a wide variety of applications in the medical field. Early detection and treatment may increase survival rates, and CT scans are the best approach to examine a lung tumor. The illness may have advanced or reached an untreatable stage when nodules are discovered. You should pay close attention to the nodule's size, tumor kind, and border type when you examine it physically. The importance of detecting and treating lung cancer early cannot be overstated. Machine learning classification might be greatly enhanced by delving into the wealth of research on image processing for lung cancer detection. Thanks to advancements in picture segmentation, it is now possible to more readily distinguish between different kinds of tumors and track the evolution of diseases. While watershed and area growth segmentation did provide encouraging results when applied to lung cancer CT images, a two-level segmentation approach could provide even more precise outcomes. It is also possible to employ support vector machines and neural networks to identify the subtype of lung cancer. By including a PSO algorithm that optimizes hyper parameters and filters into the CNN model, feature extraction may be made more adaptive. Our approach takes on tumor form and picture variability by combining the optimization capabilities of PSO with the strong feature learning of deep learning

Keywords: Computed Tomography (CT) Imaging, Watershed Segmentation, Region Growth Segmentation, Deep Learning, Convolutional Neural Networks (CNN), Particle Swarm Optimization (PSO), Feature Extraction

Introduction

Today, lung cancer ranks high among the world's most deadly diseases. Since lung cancer is often hard to identify until it has progressed to an advanced stage when symptoms do exist, the survival rate is dismal. As a result, finding problems at an early stage is crucial. Finding a way to detect cancer anywhere in the body is an enormous undertaking[1][2]. It is of the utmost importance to detect lung malignancies. Here, X-ray, CT, and sputum cytology are part of the screening process for lung cancer; computed tomography (CT) pictures are also taken into account. The medical profession makes extensive use of computed tomography. In order to improve survival rates, lung tumors should be detected and treated early. CT scans are the most effective way to do this. When nodules are seen, the disease can have progressed or become untreatable[3][4]. When you physically inspect the nodule, be sure to note its size, tumor kind, and border type. It is crucial to identify and treat lung cancer at an early stage. Looking into the mountain of literature on image processing for lung cancer diagnosis may significantly improve machine learning categorization. More accurate tumor classification and disease progression tracking are both made feasible by recent developments in image segmentation[5]. Using a two-level segmentation technique might provide even more accurate findings when applied to CT images of lung cancer, even if watershed and area growth segmentation did show promise. Subtypes of lung cancer may also be detected with the use of neural networks and support vector machines. It is possible to improve the CNN model's feature extraction by using a PSO algorithm, which optimizes hyper parameters and filters. By merging PSO's optimization capabilities with deep learning's robust feature learning, our technique tackles tumor shape and image variability[6].

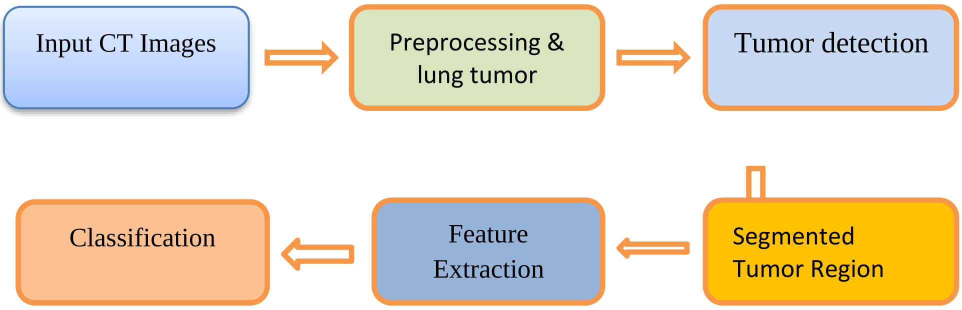

Figure 1. Typical system for identification of lung cancer

Literature Survey

Hadrien T. Gayap [3] Deep learning has shown to be an effective technique for analyzing and diagnosing medical images, particularly in the identification of cancer. This literature review compiles the most recent findings from studies that have used deep learning methods to detect and screen for lung cancer. Using a high-level overview of recent developments, constraints, and future possibilities, this paper examines deep learning's current status in detecting lung cancer. In order to provide a thorough picture of the topic, we gave preference to research that used large public datasets like LIDC, LUNA16, and JSRT. Our main area of interest is in deep learning architectures, such as 2D and 3D CNNs, dual-path networks, vision transformers (ViT), and natural language processing (NLP).

Michaela Cellina [8]. In order to reduce the time required for image interpretation, a computer-aided detection (CAD) system may automatically identify possible lung nodules with high sensitivity. This system acts as a second reader or concurrent reader. After a nodule has been found, it has to be classified as either benign or cancerous. There are two AI-based methods that can accomplish this: one uses automatic segmentation and then evaluates the size, volume, and densitometry features of the lesion; the other uses segmentation and then extracts radiomic features to describe the whole abnormality, creating a "virtual biopsy." This narrative review is an attempt to cover all the bases when it comes to artificial intelligence and lung cancer screening.

Hyuk-Jung Kwon [9] Based on cancer markers, cfDNA concentrations, ML analyses that included all multi-omics data revealed greater AUC values than analyses that analyzed each element independently, indicating the possibility of a very accurate cancer diagnosis. In conclusion, our ML analysis findings show that the model can discriminate between healthy persons and those with lung cancer, using multiomics data received from blood. This highlights the potential of the model as a diagnostic tool against lung cancer..

Zainab Gandhi [10] Author asserts in this paper that AI models can foretell how a patient will react to a therapy and help in choosing the best course of action. These models have been very helpful in optimizing radiation treatment for lung cancer patients and in predicting the chance of response and recurrence after targeted treatments.

Katarzyna Kobylińska[18] This work showcases several approaches from the area of XAI using models that evaluate the risk of lung cancer in low-dose computed tomography screenings. By using these methods, one may get a clearer comprehension of the commonalities and distinctions across BACH, PLCO*u*2012, and LCART, three prominent models used for lung cancer screening

Methodology

Preprocessing and Segmentation

Preprocessing is the first step in most image processing systems. Improving visual aspects in the given picture is the main application of eliminating noise and other undesirable components from the image[7][8]. A number of methods are used during the preprocessing step. These include modifying the input image's contrast, using auto-enhancement and the quick fourier transform, and applying noise-removal filters such as the Gabor filter[9]. Here we have the most basic level of abstraction. In some cases, the first segmentation is also part of the preprocessing. In most cases, the CT picture is converted to gray scale using a digital image processing approach that includes scaling and normalization[10].

Many filters exist for the purpose of removing noise from images; examples include low pass filters, high pass filters, etc. The anisotropic non-linear diffusion filter is one kind of noise-reduction algorithm that accounts for the CT image's edges. To make details easier to see, a picture is cleaned up using two filters the Median filter and the High boost filter—without distorting it[11]. Linear filtering is achieved by isolating each pixel in an image and computing its local mean and variance in respect to its neighbors using the Wiener filter. In contrast stretching, the initial stage in increasing the intensity of picture slices is normalizing the resultant image's value after identifying minimum and maximum intensities[12]. To separate the CT scan of the lungs into their respective halves, morphological procedures [13] as connection, dilatation, erosion, opening, and closure are used. Plus, it helps with airway removal from 3D segmented lung images and gets rid of the little linked area with logical 1 and 0 in there, which is a nice benefit.

Feature Extraction

Feature extraction is typically done in four main categories: shape, texture, intensity, and geometric properties. The most used feature extraction method is GLCM (Gray Level Co-occurrence Matrix)[10,12, 14]. It mostly includes features like contrast, correlation, clustering, energy, entropy ratio, homogeneity, and maximum correlation coefficient. Here are some examples of intensity attributes: maximum and lowest intensities, skewness, kurtosis factor, standard variance, and difference of variance [14]. Automatic correlation, fractional dimensions, maximum probabilities, sums of squares, sum variances, sum entropies, difference entropies, information measures of correlation, and inverse difference normalized are all texture aspects that may be present.

Classification

Classification is the process of putting a pixel into a predetermined category. Computers need extensive training to do what may be a trivial task for humans: pixel classification in images. Classification relies on two key ideas: feature sets and learning. Both guided and unsupervised learning are prevalent in the human brain. To reduce the likelihood of false positives and increase the accuracy of CT imaging, researchers have explored several avenues. A supervised learning model using a split hyper plane, Support Vector Machine [15].Feature set selection is taken into account when data is displayed in dimensional space; locating the hyper plane completes classification. As a classifier, random forest has the potential to differentiate between benign and malignant pulmonary nodule tumors [16]. In order to get the optimal split, a split function is used after selecting a subset of attributes for each node in the tree. As far as generic classifiers go, the most well-known one, the naive bayes classifier[17], is quite dependent on probability. The conditional probability of an occurrence is obtained by adding the unconditional probability to the conditional probability for each class. In order to create predictions, unsupervised learning classifiers such as Convolution Neural Networks[18] employ the neurons that won and lost inside the clusters. If there is a change in the cluster formation, this update may be done whenever necessary. The use of fully linked layers, maximum pooling, and convolutional layers is not out of the question. However, the user is required to specify the k-value. Classification may be approached from many different angles. Classifiers that rely on rules [19],[20] linear classifiers [20], and ANNs trained with back propagation are among them. Since medical images are captured straight from the source, they naturally include artifacts and noises including speckle, impulse, and gaussian noise. White intensity values with a normal distribution-like probability function characterize Gaussian noise. Data transmission errors produce speckle noise. It is possible for medical pictures to experience impulse noise, also known as salt and pepper noise, when they are converted from analog to digital. This sort of noise is characterized by dark pixels in bright areas and bright pixels in dark parts[7].

Watershed Segmentation Algorithm

Segmenting Image into its component parts by clustering nearby pixels is known as image segmentation. To rephrase, segmentation is a method for classifying pixels that enables the creation of picture sections with shared characteristics. Medical photographs, for example, use segmentation techniques to isolate certain anatomical or functional features. The goal of this process is to reduce the overall picture size while still preserving relevant semantic information. You can see the borders of every item in the original picture in the segmented one. Pixels belonging to the same class create a contiguous area with comparable gray scale multivariate values; this process is called segmentation[12].The values of adjacent pixels in various categories will be different. Once the picture has been filtered, it may be subjected to a segmentation algorithm. It is possible to enhance the outcomes of segmentation by using mathematical morphological approaches. In order to get quantitative data from the pictures, the segmentation findings will be used. Image segmentation techniques abound, with options such as threshold-based, edge-based, region-based, level set, clustering-based, and graph-based approaches. The computational complexity and quality of these segmentation techniques vary[14].

Particle Swarm Optimization (PSO)

A computer optimization method that draws inspiration from the social behavior of groups of fish and flocks of birds is known as Particle Swarm Optimization (PSO). By repeatedly improving a collection of possible solutions, this population-based stochastic optimization technique finds the best answer to a problem. To discover the optimal solution, PSO tries to imitate the behavior of particles traveling across a search space[15].The optimization issue of picture enhancement is solved using the PSO method. This program mimics the social behaviour of flocks of birds and is based on population based stochastic optimization. Instead of being driven by natural selection, PSO is shaped by social behavior simulations. The suggested system uses PSO, an optimization process that generates a collection of discrete solutions called particles. Each particle is a potential answer to the optimization issue, and their positions fluctuate over time. As they go through a multi-dimensional search space, particles adjust their positions based on their individual experiences. Both the best place that a particle has visited and the best position that another particle in its immediate vicinity have an impact on the particle's current location[16].

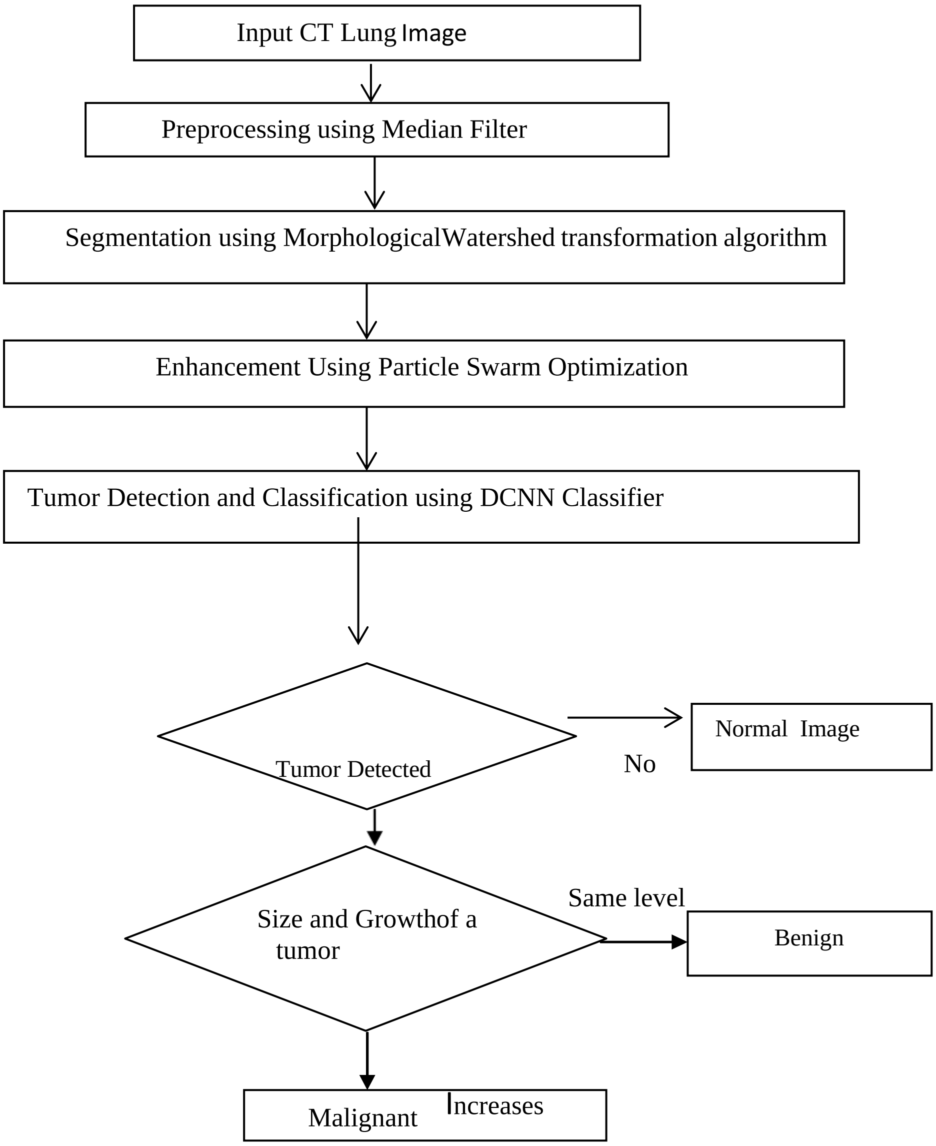

Figure 3. Proposed Project Flow Diagram

There is a higher chance of noise in the capture and transmission of images acquired by electronic equipment, such as CT scanners. Given the prevalence of various noises in post-transmission images, de-noising must be performed prior to any segmentation, feature extraction, or classification operations[17]. In this case, the noise is removed using the median filter. Figure 3 shows the results of using the morphological watershed transformation technique to subdivide a picture after noise reduction. Watershed segmentation makes use of morphological gradients and reconstruction operators to recreate gradient images. The low-value gradient pixels are subsequently eliminated, while the high-value gradient pixels are maintained. A population-based augmented optimization technique, the PSO algorithm improves the quality of the segmented image. The velocities of the particles control their flight, and the fitness values of the particles are assessed for optimization by the fitness function. Next, DCNN is used for tumor detection and classification after preprocessing. Assuming that the inputs are images enables the design to be encoded with specific attributes[18][19].

Experimental Results

From the massive set of points collected in the initial step, the centroid point is selected. The next step is to update the centroid after assigning it points according to a feature. After receiving points, the adjusted centroids are updated again in the second phase. The centroids would have discovered the most reasonable groups of points when the k-means technique was done. When using K-means with certain proximity functions and centroids, it is possible to get a scenario where the centroids remain unchanged and no points migrate across clusters[20]. Once the marker points are selected to be regional minima, the watershed algorithm is used. The watershed transform is a common tool for tackling the difficult problem of object separation in image processing. After segmentation, features are extracted from the segmented lung nodule. Regions of tumors are mainly classified by their area, perimeter, eccentricity, and average intensity.

The figure 4. shows the Watershed segmentation and identification of tumor spots

Input Image in gray scale format	Binary Image	Watershed segmentation	Tumor spots	Output Image with tumor Markings

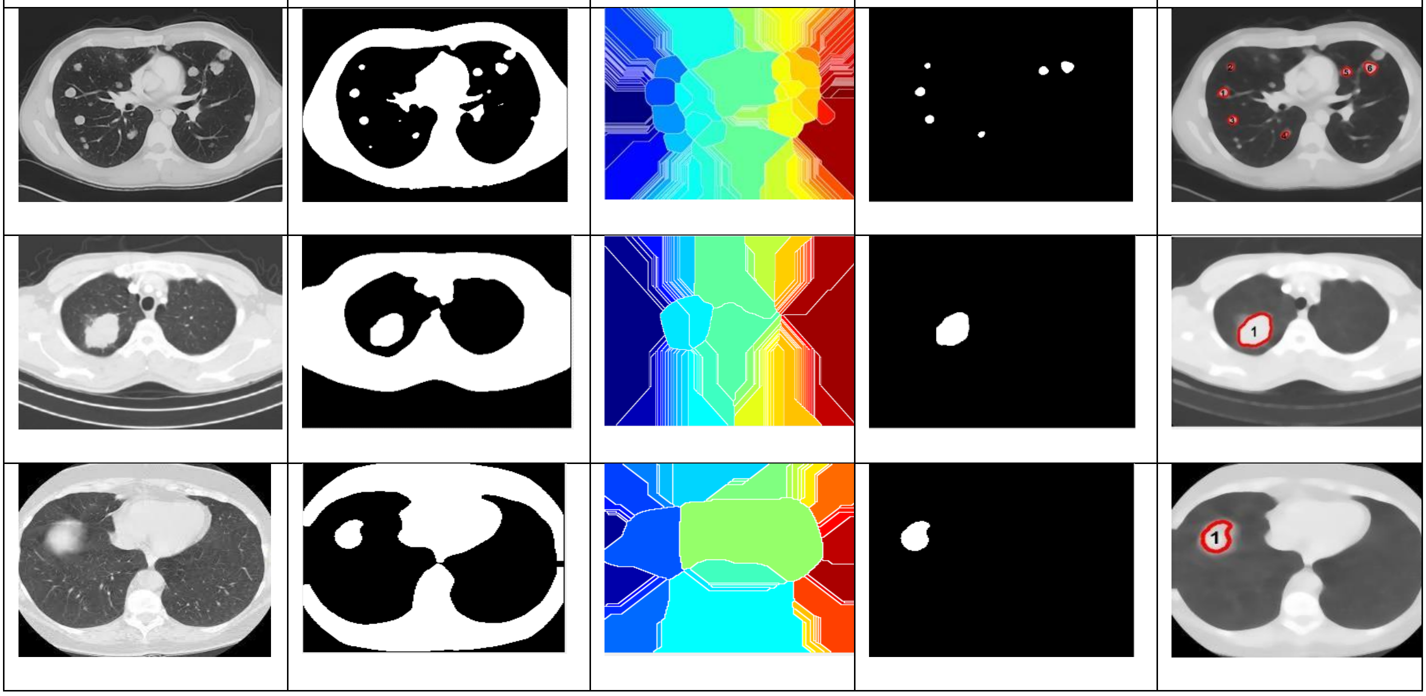

Figure 5.Data set Image Visualization

The figure 5 represents the steps involved in processing lung CT scan images to detect tumor spots using image processing techniques. Here's an explanation of each column:

1. **Input Image in Gray Scale Format**: The original lung CT scan image is converted to gray scale, which simplifies the image by removing color and retaining intensity information.

2. **Binary Image**: The grayscale image is transformed into a binary format using thresholding techniques. The pixels are classified as either white (foreground) or black (background), which helps isolate areas of interest, such as potential tumors.
3. **Watershed Segmentation**: This step involves applying the watershed algorithm, a segmentation method used to separate different regions in the image. It generates distinct regions by treating the intensity values like a topographical map and identifies boundaries between regions.
4. **Tumor Spots**: The identified regions are filtered to highlight only those that match the characteristics of potential tumors. These regions are displayed as isolated white spots on a black background.
5. **Output Image with Tumor Markings**: The tumor spots are overlaid on the original CT scan image with markings (e.g., red outlines or labels). This helps visualize the exact location of the detected tumors within the lung area.

This sequential process demonstrates how raw medical images are processed step-by-step to achieve precise tumor detection, aiding in medical diagnostics and decision-making

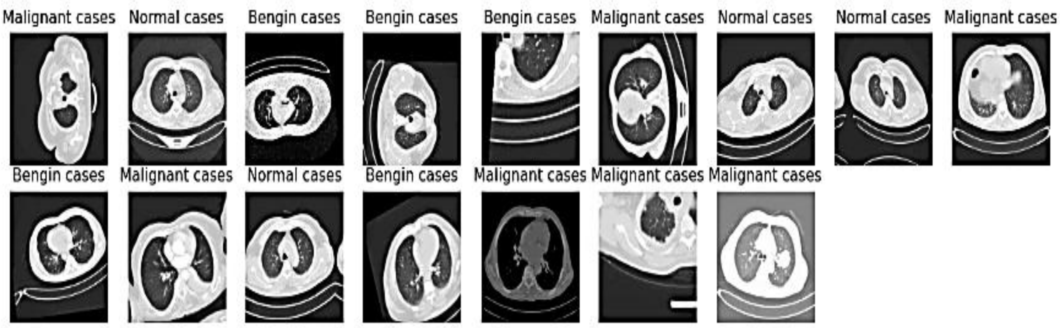

Figure 6. Lung CT Scan Dataset for Classification of Malignant, Benign, and Normal Cases

The figure 6 shows a series of labeled lung CT scan images used for classifying cases into three categories: Malignant, Benign, and Normal. The labeled dataset is crucial for supervised learning in medical imaging, specifically for lung cancer detection. It is used to train a classification model, helping the model learn the visual distinctions between malignant, benign, and normal cases. This visualization provides a clear representation of the variety of cases present in the dataset, ensuring a balanced mix for effective model learning.

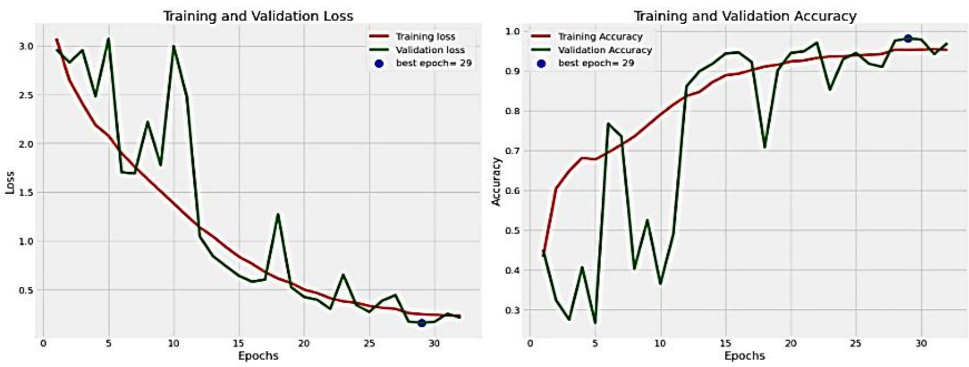

Figure 7 Display model performance

Figure 7 shows The graphs show the training and validation loss (left) and accuracy (right) over 30 epochs for a machine learning model, with the best epoch marked as 29.

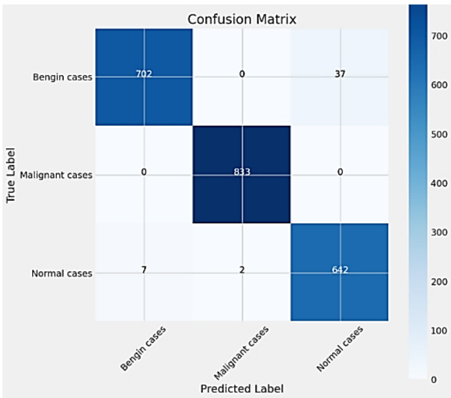

Figure 7. Confusion Matrix

	precision	recall	f1-score	support
Bengin cases	0.99	0.95	0.97	739
Malignant cases	1.00	1.00	1.00	833
Normal cases	0.95	0.99	0.97	651
accuracy			0.98	2223
macro avg	0.98	0.98	0.98	2223
weighted avg	0.98	0.98	0.98	2223

Figure 7 a Classification Report

The Figure 7a shows a classification report for a machine learning model, providing performance metrics such as precision, recall, and F1-score for three classes: "Benign cases," "Malignant cases," and "Normal cases." The accuracy of the model when it predicts a positive outcome is known as precision, and it is defined as the percentage of positive predictions that are true out of all positive forecasts. The percentage of "benign cases" is 0.99 when there were 1.00 "malignant cases" and 0.95 "normal cases. How successfully the model recognizes each class is measured by recall, which is the fraction of true positive predictions out of all real positives. The number of "benign cases" is 0.95. One thousand "malignant cases" For all classes, the F1-Score strikes a compromise between accuracy and recall by taking their harmonic mean (i.e., 0.99 in "normal cases"). The number of "benign cases" is 0.97. One thousand "malignant cases" The value for "normal cases" is 0.97.

Conclusion

Lung tumor classification using image enhancement techniques based on deep learning and particle swarm optimization (PSO). By incorporating advanced image enhancement techniques, the model is better able to distinguish relevant features in medical images, improving its ability to classify lung tumors accurately. Image enhancement aids in making subtle patterns more discernible, which is crucial for detecting malignancies. HPSO algorithm enhances the deep learning model's performance by fine-tuning hyper parameters, helping the model converge faster and achieve better accuracy. This optimization helps balance the model's generalization capabilities, thus preventing over fitting or under fitting issues. Future research can explore energy-efficient implementations of hybrid PSO and deep learning on specialized hardware like GPUs, TPUs, or FPGAs.

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