International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

A Labelled Priority based Weighted Classifier for Feature Extraction for Accurate Lung Tumour Detection using Machine Learning Technique

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Submitted: 25/04/2023 **Revised**: 25/06/2023 **Accepted**: 06/07/2023

Abstract: Lung cancer affects people of all ages and is caused by cell proliferation in the lungs uncontrollably. This leads to extreme respiratory issues both in the inhalation and exhalation of the chest. Cigarette smoking and passive smoking are the major causes of lung cancer, according to the World Health Organization. Unlike other malignancies, lung cancer mortality rates increase every day in both young and elderly persons. The death rate remains unacceptably high, despite the availability of high-tech medical installations for accurate diagnosis and successful medical treatment. Consequently, it is vital to take early steps to recognize signs and consequences early so that a more exact diagnosis may be achieved. Due to its great computational ability to forecast early disease with reliable data processing, machine learning had significant impact in recent years on the healthcare area. Numerous methods for classification of lung cancer data into benign and malignant categories are analyzed in the UCI machine learning repository to tackle existing challenges. In this paper a Labelled Priority based Weighted Classifier for Feature Extraction for Accurate Lung Tumour Detection (LPbWCFELTD) using Machine Learning Model is proposed that accurately identifies the lung tumour by considering the relevant features from the dataset. The new model is compared to established models and the findings demonstrate that the precise levels of the proposed model are better for detecting lung tumours.

Keywords: *Lung Tumor, Feature Extraction, Classification, Feature Extraction, Feature Selection, Relevant Features, Machine Learning.*

1. Introduction

Lung cancer is one of the most common causes of death worldwide. Lung cancer takes the lives of more people each year than any other form of cancer. Not only men, but also women, are affected by this dangerous disease [1]. The patient with lung cancer has a very low life expectancy since being diagnosed [2]. Patient survival probabilities are better if the procedure is done early in the development of the disease, which is why it is crucial to diagnose cancer as soon as possible. As a result, in image processing and machine learning, we can apply new techniques to produce the proper and immediate result. By increasing the number of replicas employed, the precision of the procedure can be increased [3]. The rate of survival can be improved by early detection and prediction of cancer. Mammography [4], Computerized Tomography Scan [5], and Magnetic Resonance Imaging images are among the previous techniques.

Lung cancer is treated with surgery, chemotherapy [6], radiation therapy, and immunotherapy, among other things. Despite this, the lung cancer detection procedure is very unreliable because doctors will only be able to diagnose the disease after it has spread to an advanced level. As a consequence, early detection before the final stage is crucial to lowering the mortality rate via effective monitoring [7]. Even with adequate therapy and diagnosis the rate of survival of lung cancer is quite encouraging. The survival rates of lung cancer differ from person to person. Everyone has a role to play in age, gender, ethnicity and health. In early stages of human life, machine learning is becoming useful for the identification and forecast of medical illnesses. Machine Learning simplifies and anticipates the process of diagnosis [8]. The lung tumour in MRI images is represented in Figure 1.

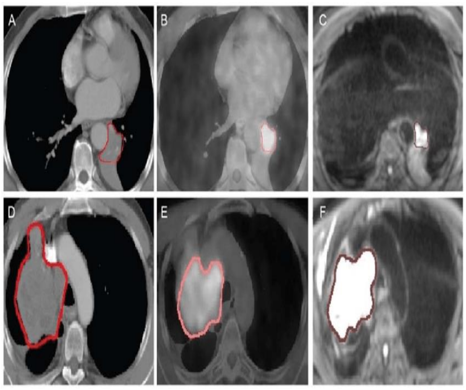

Fig 1: Lung Tumour Recognition in MRI Image

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In recent years, machine learning has already dominated the medical business. In every county healthcare business, machine learning approaches [9] are being deployed. Machine learning can be used to investigate actual disease identification. Many of the most significant machine learning applications are:

Feature Extraction: The characteristics of any disease are the genuine pot of knowledge of the condition. Machine learning (ML) makes it possible to analyse data and process real attributes or data and to determine the true causes of sickness [10]. It helps physicians pinpoint the root cause of disorders.

Image Processing: Image identification utilising various machine learning approaches has been found to be dependable and useful. This helps the clinicians concerned to make a more accurate diagnosis, saving time and money while enhancing the benefit ratio [11].

Drug Manufacturing: Medicines should be multifunctional and quantity should be known, depending on the rise in different diseases [12]. As a result, machine learning has solved the issue and is supporting the pharmaceutical industry in the use of machine learning systems in manufacturing [13].

Better Disease Prediction: Machine learning helps anticipate the severity and outcome of the disease. ML prevents disease epidemics by anticipating them in advance in order to take effective steps. In order to become more standardised and precise, machine learning techniques must also be streamlined [14]. This will help medical practitioners and health catalysts to make accurate clinical judgments with high precision [15].

Digital image processing is a technology used to change or conduct image activities to collect useful information [16]. It begins with picture pre-processing, which improves image quality through procedures such as histogram processing, log transformation, etc. Next, an image restore is done to the upgraded image with added noises like Gaussian ring, salt and pepper ring and filters are added to remove noises like medium filters, medium filters and so on based on individual ring noise [17]. The colour conversion changes after the noise has been removed, to transform the image from RGB to grey level or RGB to HSV (hue, saturation, value). After the image discussion is complete, the work of image segmentation [18] is to split the image into a component. There are numerous picture segmentation approaches, like edge detection, point detection, area-dependent detection, etc.

1.1 Feature Extraction

In digital image processing, the segmentation of images is essential since it only contains the required sections of the image. After segmentation of the image, extraction of the feature is performed [19]. Feature extraction is described as the process of decreasing the dimensionality of raw data gathering into a manageable processing group [20]. There are several feature extraction approaches, such as area based, texture based, etc. Once the features are extracted, the data are classified using machine learning techniques.

Automatic selection of features is the optimization strategy that seeks to select a subset of size that maximises some criterion functions, in the light of a collection of features. Feature selection techniques are necessary to recognise and classify systems, because the performance of the classifier decreases as far as the execution time and the recognition rate are concerned when using a wide feature space [21]. The runtime increases due to the measuring cost with the amount of features [22]. The recognition rate can be decreased due to robust functionality and the fact that the dimensionality of the training sample [23] can also be reduced by a small number of features, resulting in over workouts. On the other side a decrease in the number of characteristics might lead to a loss of discriminating and hence decrease the precision of the recognition system [24]. A certain feature selection procedure can be applied over the whole feature area, depending on the number of selected features from 1 to m, to determine the optimal feature subset for some criterion. The section 1 briefly introduce about the classification of lung tumor detection with the requirements. Section 2 provides a brief survey on the exisitng feature extraction and lung tumor classification models using machine learning. Section 3 discuss about the proposed mdoel and the working process of the proposed model. Section 4 represents the results and the evealuation parameters. Section 5 includes conclusion of the paper.

2. Literature Survey

Alcantud et al. [1] presented a study in which two types of cancer images, MRI and CT images, are used. The scan images are improved with Gabor flter, and Canny flter is used for edge detection because of its precision. Eventually, super pixel segmentation is performed. The entire medical image processing process is shielded. The features are extracted and the tumor cells are analysed for better prediction rate.

Chaubey et al. [3] employed soft computing and image processing methods to diagnose lung cancer from CT scans. The Gaussian filter and anisotropic diffusion filter approaches are used for pre-processing. For the segmentation of images, the Watershed segmentation algorithm was utilised, which is a more efficient and successful approach. The classification techniques were applied using Support Vector Machine (SVM) and the K-Nearest Neighbour (K-NN) and with a K-NN approach producing around 5.5% higher performance.

Bhatia et al. [4] explored strategies for detecting lung cancer edges in a image. The author claims that CT scans can detect lung nodules as small as 2–3 mm, and that the combination of pre-processing Gabor filters and watershed segmentation produces the best results. The Canny operator delivers the best performance for edge detection compared to other edge detection algorithms.

The subject of lung tumour detection approaches, contrasting the Gabor filter and Fast Fourier Transformation (FFT) methods performed by Arnaud et al[6], but found that the Gabor image enhancement method beats the FFT method. The Watershed Segmentation method offered roughly 4 percent better results when the step threshold approach and the Marker-Controlled Watershed Segmentation approach were compared in the picture segmentation. Binarization and masking approaches are used for extracting images, however binarization results in greater performance, are contrasted.

JunyuanXie et al. [7] carried out a research of several machine learning methods on a range of cancer data and concluded that selection and classification integration will generate promising outcomes in cancer analysis. Mario Buty1et al. [8] suggested an SV Model for the selection of protein attributes, which concluded that the result is 88 percent accurate in comparison with previous lung cancer tumour classification methodologies.

Buty et al. [11] described imagery model for predictions computed in their work. It is a typical approach for the detection and assessment of lung cancer. Expert quality evaluations on various characteristics that define the appearance and shape of a nodule are routinely employed in clinical practise to detect lung nodule malignancy, although these criteria are often subjective and arbitrarily described.

The Hussein et al. [12] approach can take two phases into account and each phase can be optimised efficiently by gradient back-propagation in depth networks if it is performed within a logical transformation function. A new dataset is being compiled comprising 131 pathological samples, the largest collection known for pancreatic cyst segmentation. The system achieves a Dice-Sorensen coefficient (DSC) of 63:44%, without human aid, which is higher than the amount achieved without deep supervision (60:46 percent). However, this strategy delivers less consistency.

Padmavathy et al. [16] employed SVM to assess if the tumour was malignant or benign. SVM was trained with these features after removing the features. After preparation, classification is done and a dispersion plot based on the expected performance is generated. For prediction, Milletari et al. [17] employed three types of SVM kernel functions: linear, polynomial and RBF. When the data collection is non-linearly structured, the kernel function is used. Because the image was nonlinear, three types of kernels were applied and the performance generated by each kernel was compared.

Bray et al. [18] has used a study database to train a artificial neural network in order to identify patterns. The Backpropagation algorithm employs the artificial neural network to identify the photos that are submitted as malignant or uncancerous. Not only does it determine whether or not the tumour is malignant, it also displays the range of the tumour. The artificial neural network, according to Yanase et al. [19] analyses texture and ruggedness from photos and carries out a precise ranking sequence with the train sets. The backpropagation algorithm was used to train a multilayer artificial neural network. Palumbo et al. [20] employed feed for neural and back propagation with various network training features for classification. Basically, the backpropagation method is trained using multiple network training functions such as gradient descent.

A.K. Alzubaidiet al.[22] devised a methodology to assess if a tumour is normal or pathological. The information gain value for decision-making is determined by means of all the input image functionalities as item sets such as transitional areas, range, morphological area, and pixels. All features with the highest standard value for knowledge have been selected for decision-making. The highest information function becomes the root node, after which it selects its child node, and so on, till the training picture set is not empty.

3. Proposed Model

The number of advantages required to characterise a broad set of data is referred to as feature extraction. When conducting an inspection request for perplexed results, the key issue emerges from the jumbled factors. The proposed research employs machine learning techniques to enhance the precision of lung tumour cell recognition.Different methods have been used to extricate pictures in order to discover feature extraction of picture geometrical and observable properties. Feature extraction is the method of sending image data to a coordinating organisation for the purpose of performing a picture mining process. Using factual techniques, image transformation, and surface-based approaches, various features can be extracted from photographs. Image handling systems are attached to the images in order to eliminate noise, which helps in the separation of lung tumour growth cells from normal cells.

The imagefeature extraction structure is a crucial development that affects the final outcome, and evaluated the ordinariness and deviations from the standard of a picture using calculations and strategies. In the proposed labelled priority based weighted classifier for feature extraction for accurate lung tumour detectionusing machine learning model, during image processing, the calculations and procedures identify and eliminate various unappealing parts or shapes (features) present in the image. The division of the lung area is completed first, followed by feature extraction to obtain its features. Finally, it is applicable with some form of determination law where tumour growth is concerned. Tumours in the lungs can be found without difficulty. These decision concepts can be used to prevent the incorrect detection of tumours caused by separation, resulting in a stronger conclusion. The proposed model framework is indicated in figure 2. The following are some of the characteristics found in demonstrative markers:

- Area of outline
- Area of interest
- Amount of nodule and
- Difference development.

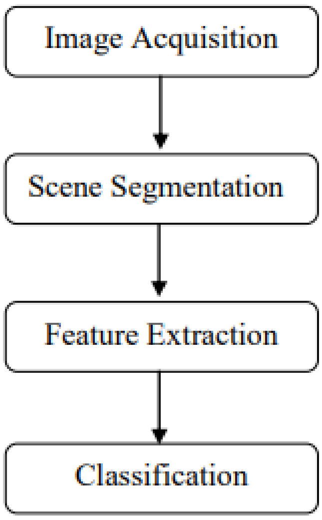

Fig 2: Proposed Model Framework

The proposed feature extraction methodology is based on calculating the histogram of the region imperativeness structure for the Image Acquisition,Image Segmentation, Feature Extraction, Classification, region of interest. The congruencystage method is used to measure neighbourhood pixel values along various presentations. The Gabor-log is referred to as

$$G(\omega) = \exp\left\{ - \frac{\left(\log\left(\frac{\omega}{\omega_o}\right)\right)^2}{2\left(\log\left(\frac{k}{\omega_o}\right)\right)^2} \right\} \quad (1)$$

Where ωo is the image boundary limits and ω is the relevant pixel , k/ωo is consistent that shifts ωo to the neighbour position.

Let G_{so}^{even} and G_{so}^{odd} be the relevant and irrelevant pixels of the image. The image vector representation is performed using the equation

$$A_{so} = \sqrt{\left(e_{so}(z)\right)^2 + \left(O_{so}(z)\right)^2} \quad (2)$$

Here 'so' is the segmentent order to extract pixels, 'z' is considered as the image considered for extraction, 'e' and 'o' represents the relevant and irrelevant pixels.

The image angle adjustments are performed for accurate pixel extraction is performed as

$$\Delta\phi_m(z) = \tan\left(\phi_m(z) - \bar{\phi}_m(z)\right) - \left|\tan\left(\phi_m(z) - \bar{\phi}_m(z)\right)\right. \quad (3)$$

Here ϕ_m is the angle of adjustment of images for accurate pixel extraction process. For the image considered, the pixels are extracted and weights are allotted for the pixels for consideration to identify the tumour region in the image. The weights are allotted as

$$W_{u,v} =$$

$$\frac{1}{m} * \sum_{x=0}^{m-1} \sum_{y=0}^{m-1} P_{x,y} * e^{2\pi\left(\frac{ux}{m} + \frac{uy}{m}\right)} + \Delta\phi_m(z) \quad (4)$$

Here x, y are the coordinate values of the image, u is the pixel intensity limit and P is the pixel extracted. M is the limit of pixels up to the image edges. After allotting the weights, the labelling of pixels is performed for considering the pixel or excluding the pixel. The process of labelling is performed as

Th

$$PL(W_{u,v}) = \frac{1}{m^2} \sum_{x=0}^{m-1} \left\{ \sum_{y=0}^{m-1} P_{x,y} e^{\left(\frac{2xy}{m}\right)} \right\} + \max(W) \quad (5)$$

The extracted pixels are arranged in the 2D matrixform with m × m pixels, then these coefficients can be calculated for easy detection of tumour region. The process is performed as follows:

$$P_{i+1,(x,y)} = \frac{1}{2}\sum_{k=0}^{m-1}\sum_{l=0}^{m-1} d_k d_l c P_{i,(2x+k,2y+l)}$$

$$N(p)_{i+1,(x,y)} = \frac{1}{2}\sum_{k=0}^{m-1}\sum_{l=0}^{m-1} b_k d_l c P_{i,(2x+k,2y+l)}$$

$$M_{i+1,(x,y)} = \frac{1}{2}\sum_{k=0}^{m-1}\sum_{l=0}^{m-1} d_k b_l c P_{i,(2x+k,2y+l)}$$

$$M(x,y) = \lambda . P^2 \sqrt{\left|\Delta_{diff}\right| \frac{W_{x,y}}{N(i)+M(i)}} \quad (6)$$

Where

$$\Delta_{diff} = \begin{cases} \Delta, if\ \Delta \geq 1 \\ -\frac{1}{\Delta}, otherwise \end{cases}$$

Where 'λ' is a scaling aspect that indicate the coefficient of change for the pixel x in thecluster and in the neighbour clusters, separately, k is the pixel coordinate threshold limit,

Filtering Data:

Input: Cancer datasets DS(1), DS(2) …..DS(n)

Output: Tumor Filtered Data

Read records from datasetsDS(1), DS(2)……DS(n)

For each record r(i)ε DS(n)

do

For each attribute A in the instance ins(i)

do

if (isNumeric (A_i)&&A_i(I) == null)

then

$$A(Ins(i)) = \sum_{j=1/i\neq j}^{n} \left(\left(\sum X_j^2\right) - \mu_{A(Ins(i))}\right) / \left(Max_{A(I}\right. \quad (7)$$

$$P(r(i)) = \frac{P(M(i)) + P(r_1 \ldots r_n)}{\Sigma_{i=1} P(M(i+1)) + W(P(i))} \quad (8)$$

Now, assuming the Mi are conditionally independent given W. The tumor cell identification is performed as

$$P(Y = yk | X_1 \ldots X_n) = \frac{P(Y = yk)\Pi_i P(X_1 | Y = yk)}{\sum_j P(Y = yj)\Pi_i P(X_1 | Y = yj)} \quad (9)$$

The training data can be estimated from the given determined attribute values of Π, and given distributions P(Y) and P(Xi/Y). The classification rule is performed as

$$Tp(DS(i)) \leftarrow \arg\max_{w,PL} \frac{P(Y = yk) + \max(W(P(i))) + X_1 * Y}{\Sigma_{i=1} P(Y = yk) + PL(P(i))} \quad (10)$$

4. Results

The proposed model is implemented in python and executed using ANACONDA SPYDER. The proposed Labelled Priority based Weighted Classifier for Feature Extraction for Accurate Lung Tumour Detection (LPbWCFELTD)model is compared with Adaptive Hierarchical Heuristic Mathematical Model (AHHMM) [2]. The MRI image dataset is considered from https://www.kaggle.com/kmader/siim-medical-images. The proposed model is compared with the traditional models by considering the parameters like Image Segmentation Time Levels, Image Pixel Extraction Time Levels, Feature Extraction Time Levels, Tumour Detection Accuracy Levels, True Positive Rate.

Image segmentation is the division of a digital image into several segments. The objective of segmentation is to simplify and/or modify the visual representation into something more relevant and easier to evaluate. Image segmentation is often used to locate images with objects and boundaries. More specifically, the technique of segmenting images is to assign a name to each pixel in an image so that pixels with the same label share particular properties. The Figure 3 represents the Image Segmentation Time Levels of the proposed and existing model.

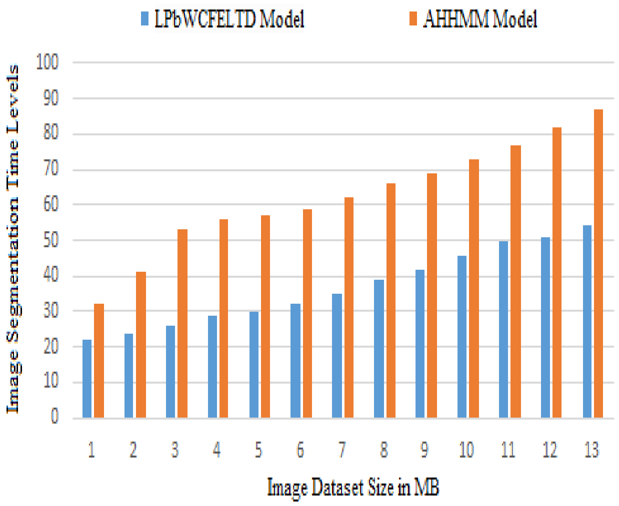

Fig 3: Image Segmentation Time Levels

After performing image segmentation, from each segment, pixels are extracted and formed as a group for accurate analysis. The Image Pixel Extraction Time Levels of the proposed and the traditional models are indicated in Figure 4.

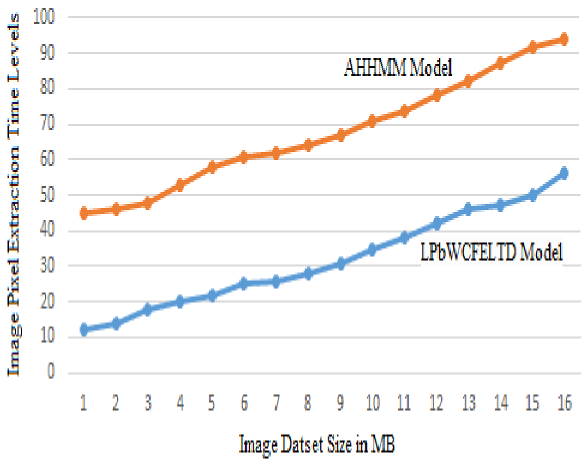

Fig 4: Image Pixel Extraction Time Levels

Feature extraction is performed here to find essential data features by acquiring additional features from the original data set. The extraction of relevant feature helps to reduce the number of redundant data in the data set. Finally, the reduction of the data helps to develop the model with less effort on the part of the computer and to boost the speed of learning and generalisation of processes. The proposed and traditional models feature extraction time levels are indicated in Figure 5.

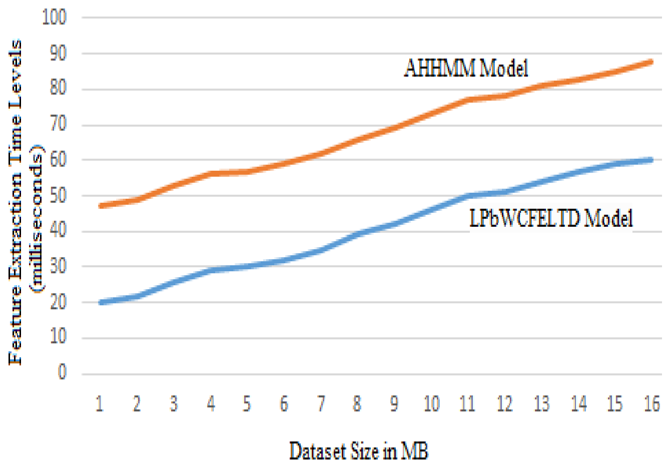

Fig 5: Feature Extraction Time Levels

The Table 1 indicates the accuracy levels of the tumour prediction from the input provided.

Table 1: Accuracy Levels

Method Used	Tumor Prediction Accuracy in (%)
KNN	79
Logistic Regression	81
SVM Model	82
AHHMM Classifier	89
LPbWCFELTDClassifier	97

The proposed model efficiently detects the lung tumour when compared to the traditional model. The proposed model extracts only relevant features thereby reducing the number of the features that reduces the time complexity. The accuracy levels of the proposed and traditional models are indicated in Figure 6.

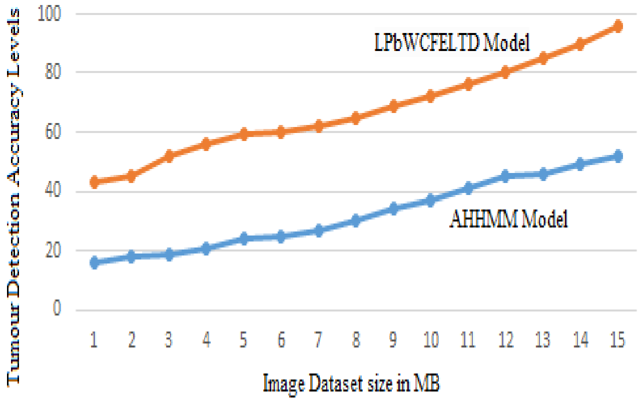

Fig 6: Tumour Detection Accuracy Levels

A true positive result means that the model predicts the positive class properly. The proposed model true positive rate is high when compared to the traditional model. The true positive rates of the proposed and traditional models are depicted in figure 7.

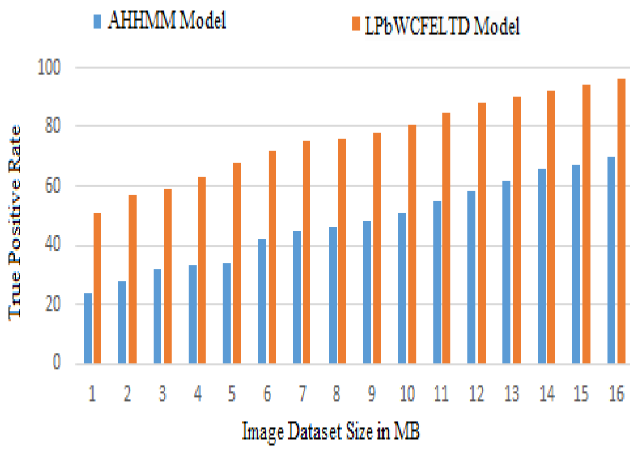

Fig 7: True Positive Rate

The table 2 indicate the numerous parameter values that indicates the performance levels of various models.

Table 2: Performance Metrics

Classifier	Sensitivity (%)	Specificity (%)	Precision (%)	False Positive Rate (FPR)	Recall	F1-score
KNN	61	62	68	0.95	0.86	0.87

Logistic Regression	65	68	72	0.87	0.76	0.75
SVM Model	76	78	63	0.68	0.81	0.76
AHHMM Classifier	79	82	81	0.81	0.74	0.55
LPbWCFEL TD Classifier	94	95	92	0.15	0.71	0.63

5. Conclusion

The death rate for lung cancer in underdeveloped nations is 22.3 percent, and it is one of the most dreadful disease. Early pulmonary tumour detection takes place using numerous imaging modalities including computed tomography, sputum cytology, X-ray chest and Magnet Resonance Imaging (MRI).Unfortunately, after spread or reaching a dangerous level, this condition is extremely difficult to treat. The adoption of image processing techniques can significantly improve the manual analysis and diagnostics system. Many researchers try an early diagnosis of cancer through the evolution of the machine learning techniques. Machine Learning is a major technique for recognising the cell of cancer in the regular tissue, providing an effective tool for the development of an assisted cancer diagnosis based on AI. The therapy of cancer can only be effective if the tumour cells are precisely isolated from normal tumour cells and training is the cornerstone for the machine-based learning diagnosis of cancer. In this manuscript, a labelled priority based weighted classifier for feature extraction for accurate lung tumour detectionusing machine learning is implemented for accurate feature extraction from the MRI images for improving the prediction rate. The specificity acquired is 96.6%, which indicates that very less false positive detection exists. Furthermore, in comparison with traditional systems, the precision, sensitivity and specificity of the suggested system is very high. The system will in the near future be trained to diagnose the type of cancer with its size and shape with massive datasets. By using the 3D Convolution Neural Network and improve hidden neurons using a depth network, the overall accuracy of the system can be increased.

Conflicts of interest

The authors declare no conflicts of interest.

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