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# Motion Prediction Model Using Adaptive Neuro Fuzzy Network (ANFN) and Probabilistic Neural Network (PNN) Algorithm in 4-Dimensional Computed Tomography (4DCT) Images

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## ABSTRACT

**Introduction:** Across the world, the major cause of death is due to lung cancer. Due to overlapping structure of cancer cell, earlier lung cancer detection is challenging. Image processing techniques are widely employed to detect lung cancer earlier.

**Objective:** Novel method to prevent and predict lung cancer as well as to identify the most significant genetic and environmental factors has to be developed.

**Methods:** The proposed system illustrates a novel predicting model using Adaptive Neuro-Fuzzy Network combined with probabilistic neural networks. Filtered image using Gaussian 3D operator has to predict the tumour growth direction. This model uses an adaptive neuro-fuzzy network and probabilistic neural network for better identification.

**Results:** Simulation result gives a prediction of Tumour growth direction with its accuracy value, precision value, RMSE (root-mean-square error), specificity, positive predictive value, negative predictive value. Hence the simulation results show the prediction of Tumour growth.

**Conclusion:** The proposed system illustrates a novel predicting model using Adaptive Neuro-Fuzzy Network combined with probabilistic neural networks. By predicting the movement of Tumour cells, it will be easier to control the tumour spreading. This can be done by the motion prediction model to reduce the growth of the tumour cells which is the contribution of this paper.

**Key Words:** Lung cancer, Motion prediction model, Adaptive Neuro-Fuzzy Network, Probabilistic Neural Networks, Predictive value

## INTRODUCTION

For significant preventive strategy and diagnosis process, early lung cancer prediction plays a vital role. There are numerous methods such as Computed Tomography (CT), Chest Radiograph (x-graph), Sputum Cytology and Magnetic Resource Imaging (MRI) Scan. Mostly, these methods are time-consuming and expensive. In advanced stages, these methods detect lung cancer in which the patient survival rate is very low. In early stages, to diagnose lung cancer there is a significant need for new technology. For enhancing manual analysis, image processing method gives good quality tool. Various stages of cancer are shown in figure 1.

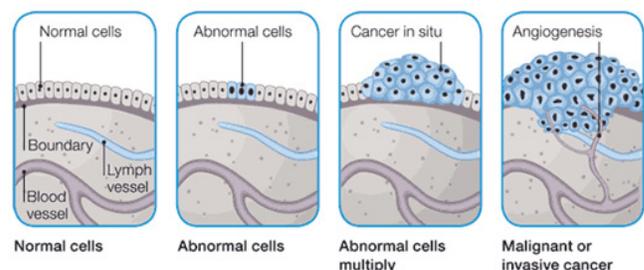


Figure 1: Stages of cancer

An efficient lung cancer prediction system has to be developed by using pattern prediction tools. Moreover, the system must be time-saving and cost effective.<sup>1</sup> For effective pre-

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vention and diagnosis process, lung cancer early prediction plays a vital role. Methods such as CT-SCAN, X-RAY and MRI are used to diagnose lung cancer which is expensive as well as time-consuming. For both men and women, lung cancer is the main death cause. Leading cause of cancer deaths was due to lung cancer which defeated the deaths of breast cancer in 1987. Due to uncontrolled cells growth, this disease occurs. When not diagnosed and treated early, it spreads to the other parts of the body like bone, brain, adrenal gland and liver.

There is no early lung cancer detection tool available as per cancer care. Small Cell Lung Cancer (SCLC) and Non-small Cell Lung Cancer (NSCLC) are major types of lung cancer. Over 85% of lung cancers are NSCLC and 13% are SCLC. When cancer is local or from lungs to other organs or lymph nodes, it is called staging lung cancer. For a longer time, Tumours grow in them due to the big size of the lungs before they found. People may think symptoms like fatigue and coughing are due to other causes.<sup>2</sup> Due to this, early stages of lung cancer are difficult to detect. At late stages, most people with NSCLC are diagnosed.

Existing methods such as CT, X-Ray, biopsy, sputum cytology, needle aspirants, electronic nose and other not need a complex tool and high cost, but it is used in the last stage when Tumour spread to other body parts. In the US, there are 0.4% by the performance of CT scans which is increased as 1.5-2% in the 2007 report. DNA damage occurs due to CT ionizing radiation which cannot rectify by cellular repair method. For diagnosing cancer, biomarker test is used but there is no specific biomarker determined for lung cancer and researchers working for it. After stage 1, mostly lung cancers are found by using exiting methods. According to other cancers, it has a 16.3% as 5 year survival rate and early detected cases are 52.6% within the lungs and 15% are diagnosed at early. It reduces to 3.5% for distant Tumours. Within one year it is diagnosed as half of the people die due to lung cancer.<sup>3</sup>

It is defined as uncontrolled cells growth present in one or both lungs or airline passages. These cells cannot develop in healthy lung tissue. The rapid growth of cancer cells suddenly forms Tumours. Almost 14% of newly diagnosed cancers are lung cancers which are the leading cause of cancer death worldwide based on the American Cancer Society. Diagnosed patients are at age of 60 years. In the world, lung cancer is a serious issue in the human body. When compared to other cancer types, it causes the highest death rate and a very low survival rate. Patients survive rate is increased by detecting cancer at an early stage. Previous studies reveal that the main cause of lung cancer is due to smoking. Mostly 85% are males and 75% are female cases which are due to smoking.<sup>4</sup>

## LITERATURE SURVEY

**Amjed S. Al-Fahoum, Eslam B. Jaber** presents an automated intelligent method for nodule classification and detection. The system has the ability for displaying the size of cancer detected, for replacing the manual measuring process by the radiologist and for calculating width and length of cancer area. During diagnosis, for radiologist cancer region margin detection is a major challenge. To represent Tumour growth, the margin is one of the features during diagnosis. To simplify the detection of region boundary, the previous study gives each detected area boundary which is subjected to observer variations. This method gives histogram which enables the radiologist to study cancer area homogeneity.<sup>5</sup>

**Tomas Krilavicius, Indre Zliobaite** presents an algorithmic method for 3D position target prediction in real-time which aims for each patient's short fixed calibration time of the process. To enhance radiation treatment precision, accurate Tumour motion predictions are used. To compensate respiratory motion in radiation treatment by managing beams or couch position. Model form from exponential smoothing family is considered, and model parameters are fitted by reducing absolute disposition error and prediction signal fluctuations (jitter). On clinical datasets with various behaviours like talking, quiet and laughing, predictive performance was calculated and validated in real-time on prototype method with respiratory motion imitation.<sup>6</sup>

**Fatemeh Nasiri and Oscar Acosta-Tamayo** reviewed different aspects of longitudinal modelization. The ultimate aim was to refine a model from a particular longitudinal function that was derived from past patients on a given dataset in a way that is generalizable for new patients with the same illness. The particular disease of this research was lung cancer and the longitudinal characteristics were Tumour volume and a set of characteristics based on tumour deformation over time. The distinction between the two groups was that the first group patients survived the treatment and decreased their Tumour size considerably. We suggested a mixed effect modelling scheme for the function modelling that allows each patient's modelling to benefit from both their patient-specific model as well as the general patient-independent model. The results showed that these modelling results in much higher predictive accuracy compared to modelling with fixed effects.<sup>7</sup>

**Ivo Bukovsky, Noriyasu Homma** presents a survey on real-time series predictive method for 3D time series lung Tumour. Predictive models such as MLP with one hidden layer and the quadratic neutral unit was studied. Real-time retraining methods studies such as Gradient Descent (GD) and Levenberg-Marquardt batch optimization learning rules are studied. It is estimated and compared methods for real-time prediction. The superiority of QNU over MLP gives computational efficiency, reproducibility and accuracy of

results. This result satisfies this study for 3DMAE accuracy of 1mm for 1-second prediction horizon in which its computation time is low when compared to real time.<sup>8</sup>

**Emre Dand** presents CAD on CT for early diagnoses to benign and malignant nodules classification. \*e consists of 4 stages. In CT images are improved, with help of a technique called Lung Volume Extraction Method (LUVEM) in which lung volumes are extracted. This is used for lung region extracting. At final, PNN classifies malign and benign with accuracy 95.91%, 94.24% specificity and 97.42% sensitivity. The proposed method gives nodule type with accuracy 94.68% even in small-sized nodules cases (3-10mm).<sup>9</sup>

**S Piramu Kailasam, M Mohamed Sathik** proposed CAD and offer 2<sup>nd</sup> opinion to radiologists in the diagnosis of CT images pulmonary nodules. For feature extraction, Deep CNN method is utilized. CNN, Histogram oriented Gradient (HOG), Local Binary Pattern (LBP) and Extended Histogram of Oriented Gradients (ExHOG) hybridizes as a combination. Using LBP, CNN and HOG combination of texture, rotation, shape and translation features are extracted. From Lung Image Database Consortium (LIDC), homogenous descriptors are used for feature extraction which is given to SVM, Decision tree, Random Forest and KNN for classifying nodules and non-nodules. Experimental result reveals that its accuracy gives better results when compared to other methods.<sup>10</sup>

**Manish Kakar, Håkan Nystrom** presented ANFIS on raw data to predict without filtering. There are numerous benefits obtained by using ANFIS prediction which uses NN and fuzzy methods. Both Linguistic and numerical knowledge combined into a fuzzy rule base by using fuzzy methods. This method shows network structure knowledge so that structure leaning methods are proposed. By using learning methods, fuzzy membership functions are tuned optimally. Compared to NN, its architecture is simple which needs optimization errors and extensive trails. Before training, through many random starts, ANFIS does not need extensive initializations and always happens in NN. To the clinical situation, respiratory prediction method was applied in this research. In that, there is a correlation between patient breathing and markers monitoring. For lung patients where breathing is observed by abdominal or spirometry straps, the precise correlation between target motion and breathing signal is explored. Breathing motion prediction model is a significant one which is important problem.<sup>11</sup>

**Frank Preiswerk, Valeria De Luca** integrated 2D ultrasound sequence data with population-based statistical motion model for predicting the respiratory motion of right live lobe. Before prediction, motion model has to be installed in 3D exhalation breath-hold liver scan. For reconstructing entire organ position in time, ultrasound images from anatomical landmarks tracked are together with the model are

used. In real-time, the prediction is both temporal and spatial are estimated on ground truth for a longer time of about 5.5 min. It was validated with eight volunteers where ultrasound images were acquired synchronously with 4D-MRI, which gives ground-truth motion. Tumour locations within clinically acceptable margins are predicted with average spatial prediction accuracy of 2.4 mm.<sup>12</sup>

**Ayushi Shukla, Chinmay Parab** proposed image processing based cancer prediction method. This method aims to give prior warning to users and also time and cost-saving to users. To find objects, image processing edges are used.

By using cancer CT scan images, this method identifies cancerous nodules in lung. From CT scan images, physicians use naked eye to detect spread and growth of these nodules. It is quite tedious and incorporate human error in detection. This method automatically identifies and detects cancer cells in lungs. For proper medication and finding cancer affected area, this method helps to find the pattern and shape of the pattern of the nodule to give necessary data. It also determines unnoticed cells by human eyes. Since lung cancer detection at an early stage is difficult but this method achieves early detection and increases patient's survival rate. This method not only reduces human error but increases accuracy up to 90%.<sup>13</sup>

**Keziah T A, Haseena P** improved grayscale converted lung CT scan image since all regions are darker or lighter using CLAHE. By using Modified Fuzzy Possibilistic C-Means clustering method similar and dissimilar regions are retrieved. Using the sequential forward selection method, 18 features are extracted from the Gray Level Co-occurrence matrix and best value is selected. Using SVM, lung image is classified as normal or abnormal based on selected features. If it is the abnormal affected region is extracted. This process is executed in MATLAB.<sup>14</sup>

**Marcus Isaksson and Joakim Jalden** proposed predicting position issue when moving lung Tumour during respiration. For tracking, beam gating and other dynamic management method external breathing signals are used in radiation therapy. To observe the position of Tumour with external surrogate makers, this method uses NN filters in which predict motion simultaneously with ahead time. For observing Tumour motion with external chest markers movement during free-breathing, one pancreatic cancer and 2 lung cancer patients with upper/mid lobe tumours were fluoroscopically imaged. To simplified filter linear versions, these results are compared. From surrogate breathing signal, predicting tumour position task is complicated by instability and variability in human respiration. When presented with non-stationary breathing motion, results of this method revealed that adaptive signal processing produced better accuracy rates Tumour position value than simple stationary filters.<sup>15</sup>

## RESEARCH METHODOLOGY

By predicting the movement of the tumour cell, it will be easier to control the tumour spreading. This can be done by the motion prediction model to reduce the growth of the tumour cells which is an importance of this paper.

The proposed system illustrates a novel predicting model using Adaptive Neuro-Fuzzy Network combined with probabilistic neural networks. The architecture is given below in figure 2.

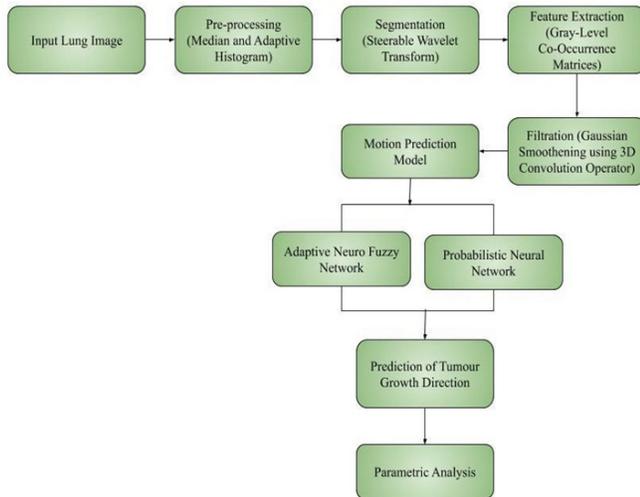


Figure 2: Proposed Architecture.

The above figure gives the proposed structure for the motion prediction model that can reduce the growth of tumour cells. Filtered image using Gaussian 3D operator has to predict the Tumour growth direction. This model uses an adaptive neuro-fuzzy network and probabilistic neural network for better identification. By have parameter analysis of these two methods it can predict the direction of Tumour growth.

### Adaptive neuro-fuzzy network (ANFN)

In this  $X$  is considered as object and it provides the general element as  $x$ . For the classical set,  $A$  those elements are defined as  $A \subseteq X$  or else objects for elements it is defined as  $x \in X$  where every element  $x$  belongs to an individual element in  $A$  set.

Through characteristics function estimation of every element  $x$  in object  $X$  the classical set  $A$  is given by the list of order pairs as either  $(x,0)$  or  $(x,1)$ . For elements,  $X$  order pair  $A$  is defined as  $x/\in A$  or  $x \in A$ . In the other hand, the fuzzy set provides the element fuzzy set by which fuzzy characteristics function provides the value between 0 and 1. Here the membership element is stated as a fuzzy set of  $A$  lies in  $X$  with ordered pair with the equation as defined in 1.

$$A = \{(x, \mu_A(x)) \mid x \in X\}. \quad (1)$$

In above equation 1, for fuzzy set  $A$ , its membership function (MF) is represented as  $\mu_A(x)$ . The MF each elements  $X$  mapped over membership grade between the range of 0 and 1. In this,  $X$  denoted as a universal factor and MF is a generalized bell or bell MF with specified parameters  $\{a, b, c\}$  those are stated in equation 2.

$$\text{Bell}(x; a, b, c) = \frac{1}{1 + \left\| \frac{x-c}{2ba} \right\|^{2b}} \quad (2)$$

Where  $b$  is always a positive value. With a selection of desire bell  $\{a, b, c\}$  for elements MF is estimated. In ANFIS, elements continue to reduce based on error function ranges between values obtained for output and calculated.

This research developed a neuro-fuzzy model with ANFIS for estimation of multilayer neural fuzzy system. The developed layer consists of five layers with a connected structure. Among those multilayer structure input and output, the layer is represented as training and prediction values. In the fuzzy interface system, the hidden layer of the network is based on the function of membership function (MFs) with a set of rules. The ANFIS fuzzy architecture provides advantages and limitation in normal feedforward multilayer network, where it is difficult to perform modification in the network.

Let us assume, the fuzzy interface system incorporates two inputs such as  $x$  and  $y$  and one output. In the first-order Sugeno fuzzy model with a common set of if-then, the fuzzy rule is generated as

Rule 1: If  $X$  is  $A_1$  and  $Y$  is  $B_1$ , then  $f_1 = P_1X + Q_1Y + r_1$ , Rule 2: If  $X$  is  $A_2$  and  $Y$  is  $B_2$ , then  $f_2 = P_2X + Q_2Y + r_2$ .

Usually, different layer of ANFIS incorporates different number of nodes. In ANFIS each node is either fixed or adaptive layer. The different ANFIS layer with associate rules are stated as below:

**Layer 1:** Each node acts as adaptive node in this layer. Also, this layer parameters are defined as premise parameters.

**Layer 2:** Each node within this layer are fixed node with label  $\Pi$ , the output of this layer is a product of all incoming signal. Each node in this layer is represented as a firing rule strength.

**Layer 3:** In this layer, every node  $N$  are fixed for assigned labels. This layer provides firing strength for the  $i^{\text{th}}$  node with a set of  $i^{\text{th}}$  rules. Hence this layer provides normalized firing value for output.

**Layer 4:** This node provides a node value of  $I$  with consideration of adaptive node. With consequent parameter analysis, this node performs processing.

**Layer 5:** Here, nodes are fixed and assigned with label  $\xi$ , which computes summation of overall output for incoming

signals.

The hybrid learning algorithm developed based on ANFIS involved in performance the gradient descent and least-square method. Precisely, in feed-forward network hybrid algorithm output nodes reaches till layer 4 and consequent parameters are estimated through the least-square method. In feed backward network, the error signal is propagated backwards and corresponding premises are updated through gradient descent. Those consequent parameters are optimized with a set of conditions with a fixed number of parameters. The main advantage of the hybrid approach is faster convergence with a reduced search space dimension. This uses backpropagation algorithm for processing.

Through linear combination overall output is estimated with consequent parameters, In ANFIS error in train set is measured using equation 3:

$$E = \sum_{k=1}^n (f_k - f'_k)^2 \tag{3}$$

$$k=1 \quad k$$

Where  $f_k$  and  $f'_k$  are the  $k^{\text{th}}$  represents desire and estimated input, and  $n$  denoted training set the total number of pairs for input and output.

### Probabilistic Neural Network

A PNN neural network is a feed-forward system, which operates based on Kernel Fisher Discriminant Analysis. This Kernel Discriminant analysis integrates Bayesian network and statistical algorithm. The operation of PNN is based on two assumptions such as each probability density function for classification is of the same type, then it is considered as Gaussian distribution and also it is represented as the normal distribution. Each classification performed with Gaussian distribution probability density function is based on a covariance matrix which means all diagonal values are the same.

A PNN network comprises of  $d$  input units,  $c$  category units and  $n$  pattern units. In PNN every pattern forms inner product through weighted vector and normalized pattern vector  $X$  is represented as  $z = w^t x$  and emits  $\exp [(z-1)/\sigma^2]$ . In this,  $\sigma$  denoted parameter set based on user and those values are equal to  $\sqrt{2}$  times of Gaussian window. Each category units form a connected pattern with insured activity in each layer and represented as Parzen window density with the estimation of circularly symmetric Gaussian window with a covariance value of  $\sigma^2 I$ . Usually, node  $I$  am defined as  $d \times d$  identity matrix. The PNN structure is illustrated in figure 3 with  $j^{\text{th}}$  pattern as  $x_{jk}$  and corresponding weights are represented as  $j^{\text{th}}$  pattern unit  $w_{jk}$ , for  $j$  ranging from 1 to  $n$  and  $k$  from 1 to  $d$ .

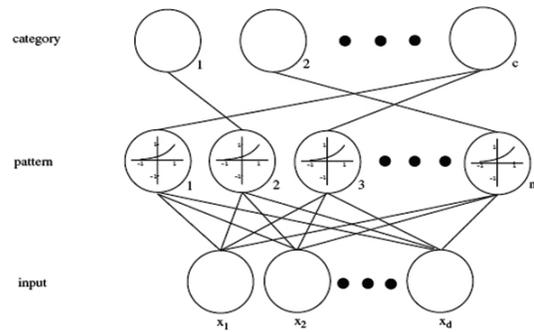


Figure 3: PNN structure.

### PNN Training Algorithm

Algorithm 1: PNN Training

Begin

initialize  $j = 0, n = \text{pattern count}$  do  $j = j + 1$

Normalize:  $x_{jk} \leftarrow x_{jk} / (\sum^d x^2)^{1/2}$

$i \quad j \quad i$

Train:  $w_{jk} \leftarrow x_{jk}$

If  $x \in w_i$  then  $a_{ic} \leftarrow 1$

Until  $j = n$

end

For classification of  $X$  pattern, each pattern needs to be located at input units. Further, every pattern needs to compute inner product  $z_k = w^t x$  with the elimination of nonlinear function  $z_k$ . Every pattern unit contributes based on the associated category for the input probability for the test function of the image with consideration of Gaussian centre related to training. The local estimation is based on consideration of local points with consideration of estimation such as to discriminate function  $g_i(x)$  with Parzen window estimation with underlying distribution function. The maximal  $g_i(x)$  offers an operational point of functional category estimation [26].

## RESULTS AND DISCUSSION

4-D images showing the direction of Tumour growth:

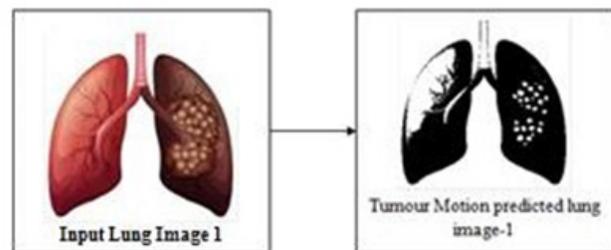


Figure 4: Lung image-1 showing the Direction of Tumour.

Figure 4 shows the lung input image-1 and its direction of Tumour growth using the proposed motion prediction model.

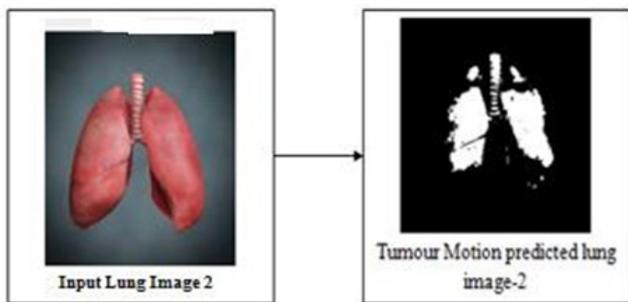


Figure 5: Lung image-2 showing the Direction of Tumour.

Figure-5 shows the lung input image-2 and its direction of tumour growth using the proposed motion prediction model.

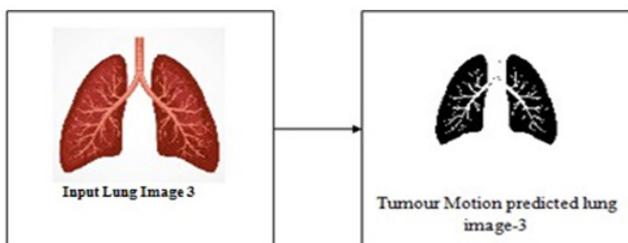


Figure 6: Lung image-3 showing the Direction of Tumour.

Figure-6 shows the lung input image-3 and its direction of tumour growth using the proposed motion prediction model.

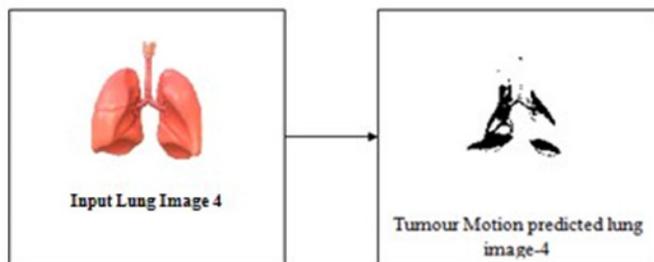


Figure 7: Lung image-4 showing the Direction of Tumour.

Figure-7 shows the lung input image-4 and its direction of tumour growth using the proposed motion prediction model.

### PERFORMANCE ANALYSIS

Table 1 presents the performance of existing and proposed models for various parameters with image 1 whose pixel count is 256 x 256.

Table 1: Comparison of image 1 with existing and proposed methods

Parameters Used	ANFIS (Linear Discriminant)	3-D Euclidean	ANFIS Motion Prediction Model
Accuracy	78.4	84.3	91
Specificity	76.4	94.6	91
Precision	88.4	85.4	90
RMSE	48.5	68.3	41.64
PPV	88	76	84.55
NPV	77.6	68.4	36.462
Mean Motion	31.2	27.6	23.46

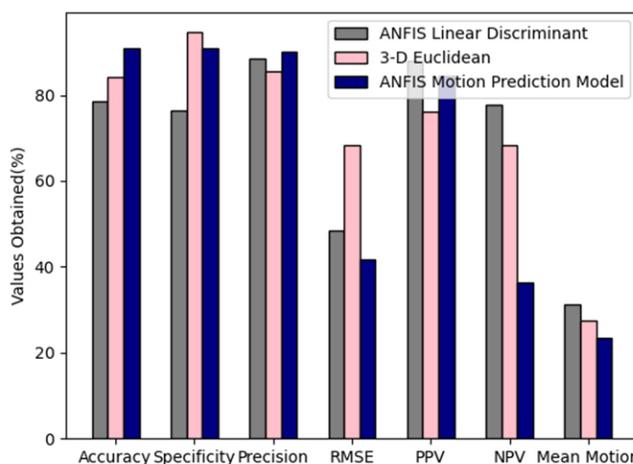


Figure 8: Comparison for image 1 with existing and proposed methods.

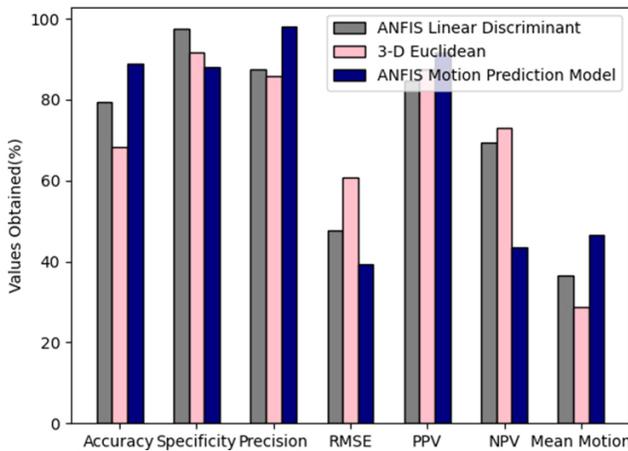
Figure 8 shows that comparison of accuracy, specificity, precision, RMSE, PPV, NPV and Mean Motion for existing and proposed methods. X and Y-axis represents the parameters used and values obtained respectively. Grey, Pink and Blue colours indicate ANFIS linear discriminant, 3D Euclidean and ANFIS motion prediction, model. Table 2 presents the performance of existing and proposed models for various parameters with image 2 whose pixel count is 256 x 256.

Table 2: Comparison of image 2 with existing and proposed methods

Parameters Used	ANFIS (Linear Discriminant)	3-D Euclidean	ANFIS Motion Prediction Model
Accuracy	79.5	68.4	89
Specificity	97.6	91.6	88
Precision	87.6	85.7	98

**Table 2: (Continued)**

Parameters Used	ANFIS (Linear Discriminant)	3-D Euclidean	ANFIS Motion Prediction Model
RMSE	47.6	60.7	39.45
PPV	84.6	87.4	91.56
NPV	69.4	72.9	43.46
Mean Motion	36.5	28.6	46.45



**Figure 9:** Comparison for image 2 with existing and proposed methods.

Figure 9 shows that comparison of accuracy, specificity, precision, RMSE, PPV, NPV and Mean Motion for existing and proposed methods. X and Y-axis represents the parameters used and values obtained respectively. Grey, Pink and Blue colours indicate ANFIS linear discriminant, 3D Euclidean and ANFIS motion prediction, model.

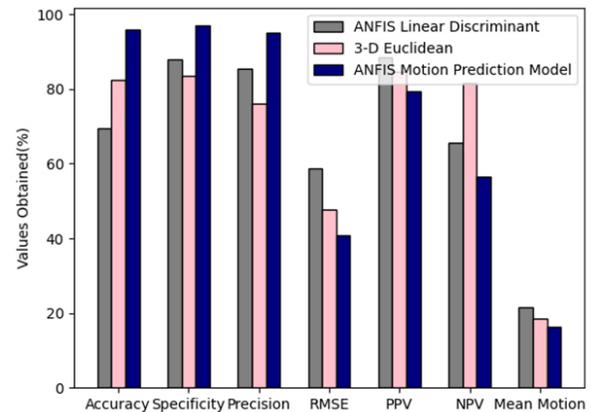
Table 3 presents the performance of existing and proposed models for various parameters with image 3 whose pixel count is 256 x 256.

**Table 3: Comparison of image 3 with existing and proposed methods**

Parameters Used	ANFIS (Linear Discriminant)	3-D Euclidean	ANFIS Motion Prediction Model
Accuracy	69.4	82.4	96
Specificity	87.9	83.6	97
Precision	85.6	76.1	95
RMSE	58.7	47.6	40.78
PPV	88.6	84.7	79.45
NPV	65.6	81.6	56.49
Mean Motion	21.6	18.5	16.45

Figure 10 shows that comparison of accuracy, specificity, precision, RMSE, PPV, NPV and Mean Motion for existing and proposed methods. X and Y-axis represents the parameters used and values obtained respectively. Grey, Pink and Blue colours indicate ANFIS linear discriminant, 3D Euclidean and ANFIS motion prediction, model.

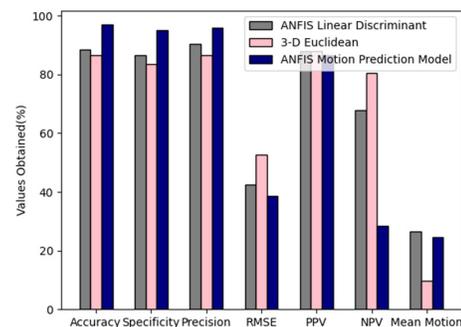
Table 4 presents the performance of existing and proposed models for various parameters with image 4 whose pixel count is 256 x 256.



**Figure 10:** Comparison for image 3 with existing and proposed methods.

**Table 4: Comparison of image 4 with existing and proposed techniques**

Parameters Used	ANFIS (Linear Discriminant)	3-D Euclidean	ANFIS Motion Prediction Model
Accuracy	88.5	86.5	97
Specificity	86.45	83.65	95
Precision	90.4	86.7	96
RMSE	42.6	52.7	38.75
PPV	88	88	86.49
NPV	67.8	80.6	28.46
Mean Motion	26.5	9.6	24.445



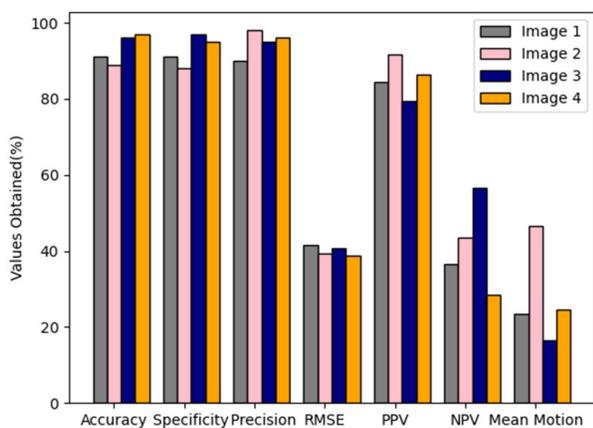
**Figure 11:** Comparison for image 4 with existing and proposed methods.

Figure 11 shows that comparison of accuracy, specificity, precision, RMSE, PPV, NPV and Mean Motion for existing and proposed methods. X and Y-axis represents the parameters used and values obtained respectively. Grey, Pink and Blue colours indicate ANFIS linear discriminant, 3D Euclidean and ANFIS motion prediction, model.

Table 5 illustrates the comparative analysis of proposed models for all input 4 images whose pixel count is 256 x 256 with various parameters.

**Table 5: Comparison analysis of ANFIS Motion Prediction Model**

Parameters Used	Image 1	Image 2	Image 3	Image 4
Accuracy	91	89	96	97
Specificity	91	88	97	95
Precision	90	98	95	96
RMSE	41.64	39.45	40.78	38.75
PPV	84.55	91.56	79.45	86.49
NP	36.462	43.46	56.49	28.46
Mean Motion	23.46	46.45	16.45	24.44



**Figure 12:** Comparison of proposed ANFIS Motion Prediction Model for various images.

Figure 12 shows that comparison of accuracy, specificity, precision, RMSE, PPV, NPV and Mean Motion for proposed ANFIS motion prediction methods. X and Y-axis represents the parameters used and values obtained respectively. Grey, Pink, Blue and orange colours indicate Image 1, 2, 3 and 4 respectively.

### CONCLUSION

Hence the simulation results show the prediction of Tumour growth. By predicting the movement of Tumour cells, it

will be easier to control the Tumour spreading. This can be done by the motion prediction model to reduce the growth of the Tumour cells which is an importance of this paper. The proposed system illustrates a novel predicting model using Adaptive Neuro-Fuzzy Network combined with probabilistic neural networks. Simulation result gives a prediction of Tumour growth direction with its accuracy, specificity, precision, RMSE (root-mean-square error), Positive predictive value (PPV), negative predictive value (NPV) and means motion.

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