RESEARCH PAPER

An Artificial Intelligence model for the prediction of Oral Cancer Lesions using Hybridized Fuzzy Logic and Deep Learning Techniques

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Received: 24th April, 2026; Revised: 20th May 2026; Accepted: 30th June, 2026; Available Online: 10th July, 2026

ABSTRACT

The World Health Organisation report (2022) says that India ranks third in lip and Oral cavity cancer out of top fifteen cancers. The statistical data given by International Agency for Research on Cancer records that 100,000 incidences occur annually with high mortality rate. The histopathological test performed using tissue cells for Oral Squamous Cell Carcinoma (OSCC) is time intense and extremely dependent on experts may lead to diagnostic deviations due to greater workload. In order to overcome the challenges, the research proposes an Artificial Intelligence model that integrates the Fuzzy Logic (ANFIS) and the deep learning algorithms. The hybrid model is analysed using the performance metrics with an accuracy of 98.75%. Earlier the diagnose and treatment reduce the mortality rate of the humans and also increases the survival rate of the patients.

Keywords: *Artificial Intelligence, Deep learning, Fuzzy logic, oral cancer, CNN, ANFIS*

How to cite this article: Kirubabai MP., An Artificial Intelligence model for the prediction of Oral Cancer Lesions using Hybridized Fuzzy Logic and Deep Learning Techniques. Int J Drug Deliv Technol. 2026;16(7): 358-362. DOI: 10.25258/ijddt.16.7.36

Source of support: Nil.

Conflict of interest: None

I. INTRODCUTION

The utmost common cancers affecting the head and neck area is oral cancer, which is a significant worldwide health concern. Out of various cancers, OSCC records nearly 90% cases with high mortality and the morbidity. As per the Agency for Research on Cancer, consumption of tobacco, usage of alcohol and chewing of the betel quid are highly predominant. The survival of the patience can be improved by earlier diagnosis with accuracy. However, the histopathological evaluation of oral lesions was time laborious. Now a days current advances in artificial intelligence in particular deep learning has marked its resounding success in the analysis of medical images. CNN models were implemented to analyse the characteristics of complex tissues. Few of the researchers have detailed as, the deep learning techniques were used for the identification and classification of oral cancer images. Even because of its performance, it acts a black box with limited perception in predictions. Due to the dearth in interpretability, it becomes challenging for the physicians for gaining trust of the healthcare professionals.

Fuzzy logic offers an efficient method for treating ambiguity and uncertainty in medical images. ANFIS architecture combines neural network and fuzzy systems allowing automatic generation of data. ANFIS classifier is applied in medical and biomedical applications for highly analytical accuracy and reasonable decision analysis. Due to increased exponentiality with the greater input features the ANFIS classifier cannot be directly applied. In order to handle the limitations, PCA is implemented for reducing the redundancy and processing complexity. The research proposes a hybrid approach of CNNFIS, where ANFIS classifier is used for identifying the levels of histopathological images. EfficientNet-B0 is implemented as the backbone of in order to extract the tissue features from histopathological images.

The proposed contribution of the research is the creation of an innovative hybrid CNNFIS classifier for the diagnosis of oral cancer, the integration of PCA in combination with fuzzy systems, generate fuzzy rules, and evaluate the proposed model using the performance metrics, like accuracy, F1-score, precision, specificity, and recall. The proposed research is predicted to aid an efficient and clear decision-making system for early detection and classification of oral cancer.

II. LITERATURE REVIEW

Oral cancer, ranks third out of top fifteen cancers, that causes mortality and morbidity across the globe and registers 100,000 incidences in India [1]. The standard used to diagnose the Oral squamous cell Carcinoma (OSCC) is the inspection of the tissues. The treatment of Oral cancer is significantly operative and life-threatening [2]. The identification and the stages of oral cancer is directly related to the survival rate of the patients with oral cancer [3]. Artificial Intelligence (AI) mimics human brain where the deep learning is in advance the subcategory of Artificial Intelligence. The data that was processed were exactly accurate consisting large volume of data representing complex relationships with complex

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structures [4]. Novel researches were steered in the real time applications of Deep Learning especially oral cancer in health care [5]. The algorithms in machine learning like random forest, support vector machine, k-nearest neighbours, Naïve Bayes, and Data Language models were implemented [6-8]. However, its appearance of medical dataset is uncertain and unpredictable, challenging in the health care field namely medicine [9]. To overcome the uncertainties the fuzzy logic system is incohesive with DL and implemented with the recent techniques called the artificial neural networks, deep learning, robotics and genetic algorithms, providing a powerful model to solve complex applications. The Convolution Neural Network Fuzzy Inference System which was implemented for table data, where the vector features were mapped to image. Hence the features values were mapped to their relative membership values [10].

III. RESEARCH GAP

Through numerous researches were assesed out on oral cancer on execution of machine learning and oral cancer algorithms there exists areas to pay attention. Researches related to images like clinical and radiographic images were carried out. The histopathological images, were minimally explored due to difficult handling of greater pixel values and of larger sizes with the cells and tissues. The CNN model and ANFIS classifier has its own advantages. The ANFIS classifier uses the fuzzy rules for prediction of data and images as well as classification. The data is interpretable using the fuzzy rules and has the advantage of handling uncertainty and impression. It provides explainable decisions for classifying the data. The CNN inevitably extract the features from the images and complex data structures and the major application of the CNN model is the pattern recognition. It is used for handling highly dimensional data and also it learns from the hierarchical features. Hence the ANFIS classifier can be hybridised with the CNN model for greater accuracy. The proposed hybridised model combines the CNN and ANFIS architecture for the extraction of features by CNN and the prediction and classification can be implemented using the ANFS classifier.

IV. CNNFIS ARCHITECTURE

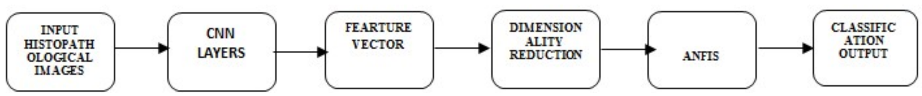

Fig. 1 CNNFIS Architecture

THE STEPS INVOLVED IN ORAL CANCER

Step 1: Image Acquisition

The input histopathological images were given as input from the datasets available in public domain and from the histopathological slides collected. The images collected are normal images, dysplasia and the OSCC images.

Step 2: Image Preprocessing

The pre-processing method improves the quality of the images and standardise the images. The size of the images is resized into 224*224 pixels which is the standard input size for the EfficientNET-B0. The data augmentation is performed to increase the data diversity like rotation, zoom and brightness adjustment. The augmentation benefits the model generalisation and also prevents overfitting.

Step 3: CNN Feature Extraction

The traditional models like VGG16, ResNet50 and EfficientNet-B0 is analysed. The VGG16 model implements 138 parameters with depth of 23 layers, where the usage of more parameters involves the increase in learning capacity whereby increases the higher computational speed. ResNet50 can also be implemented, but while hybridising with ANFIS classifier, EfficientNet-B0 works better with efficiency and accuracy. The CNN automatically extracts the feature as low, middle and high-level features. The low-level features extracted with the Edges, Corners and Color variations. The mid-level features with cell shapes and nuclear boundaries and the high-level features like tissue architecture and tumour invasion patterns.

Step 4: Global Average Pooling

Rather than using the entire connected network, the feature images were globally pooled with 1280 features. The implementation of **Global Average Pooling (GAP)** reduces parameters and overfitting that produces a compact future vector.

Step 5: Principal Component Analysis

The fuzzy rule is extremely large, and hence to achieve the significant features the Principal Component Analysis (PCA) is implemented to retain the most significant features. PCA was the widely used process to show the features in vizualisation, pre-processing and dimensionality reduction. 1280 features were reduced to 20 features using PCA where these features have 90-95% of data variance.

Step 6: ANFIS Classification

An artificial intelligence technique, **Adaptive Neuro-Fuzzy Inference System (ANFIS**) hybrids the artificial neural networks (ANN) and fuzzy logic. This ANFIS classifier automatically learns from the training data set with the benefits of understandability and transparency unlike the CNN implements like a black box model. The PCA acts as an input for the principal component analysis. Every input feature is characterised using the fuzzy membership functions as low, medium level and high that quantifies the degree the features belong to the category. ANFIS gauges the fuzzy inputs using the fuzzy rules. By hybridising the deep learning and ANFIS classifier with fuzzy reasoning, ANFIS gives an effectual and comprehensible approach for the classification of medical images, significantly implemented in decision support systems.

Step 7: Fuzzy Rule Generation

If the nuclear size is high and the texture roughness is high then it indicates that it is OSCC. If the nuclear size is medium and the texture uniformity is also minimum then it denotes dysplasia. When the nuclear size is low and the texture uniformity is also low then it denotes the normality. Hence these rules are interpretable which is usually missed in the deep-learning techniques.

Step 8: Defuzzification and Final Prediction

Defuzzification is the concluding step of the ANFIS architecture as the fuzzy outputs that were produced using the inference system is converted into the class label. On fuzzification, and rule evaluation the ANFIS figures the involvement of every fuzzy rule towards the output classes. These contributions generate the confident scores that denotes the input image of every class.

Table 1: Confidence Score

S.No.	Class	Confidence Score
1	0.10	Normal
2	0.25	Dysplasia
3	0.65	OSCC

The confident score with 0.10 shows the normal images, and score with 0.25 denotes dysplasia and the score with 0.65 denotes the images are OSCC.

V. RESULTS AND DISCUSSION

Dataset Distribution Table

Table 2. Distribution of Histopathological Images

Class Type	Training Dataset	Validation	Testing Dataset	Total
Normal	800	100	100	1000
Dysplasia	800	100	100	1000
OSCC	800	100	100	1000
Total	2400	300	300	3000

The class levels are categorized into normal, dysplasia and OSCC images, consisting of 2400 training images, 300 for validation and 300 for testing the images.

CNN Training Performance

Table 3. EfficientNet-B0 Training Results

Epoch	Training Accuracy (%)	Validation Accuracy (%)	Training Loss	Validation Loss
10	82.4	80.2	0.52	0.58
20	89.7	87.9	0.31	0.35
30	94.8	92.3	0.16	0.21
40	97.1	95.4	0.09	0.12
50	98.2	96.7	0.05	0.08

The table gives the overall view of the training accuracy and validation accuracy.

Performance Metrices for the Classification Performance

Table 4. CNN-PCA-ANFIS Multiclass Classification Performance

Class	Precision	Recall	F1-Score	Specificity
Normal	0.95	0.96	0.95	0.98
Dysplasia	0.93	0.91	0.92	0.97
OSCC	0.97	0.96	0.96	0.99
Average	0.95	0.94	0.94	0.98

The table gives the performance metrices of precision, recall, F1-Score and Specificity.

Confusion Matrix

Table 5. Confusion Matrix

Actual / Predicted	Normal	Dysplasia	OSCC
Normal	96	3	1
Dysplasia	4	91	5
OSCC	1	3	96

The table depicts that the images that were normal were correctly identified as 96, and Dysplasia images are 91 and the OSCC images were 96.

ROC CURVE

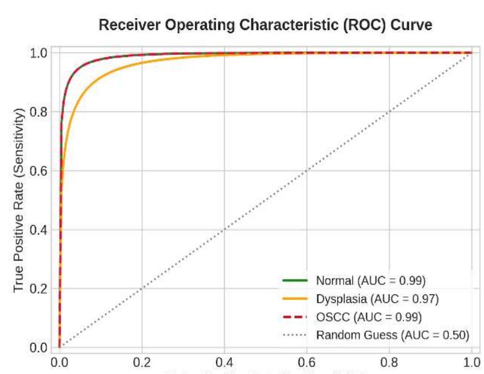

Fig. 2 AOC Curve

Comparative Study Table

Table 6. Comparison of Classifiers Comparative Study Table

Model	Accuracy (%)	Precision	Recall	F1-score	AUC
SVM	86.5	0.85	0.84	0.84	0.89
Random Forest	89.3	0.88	0.88	0.88	0.92
CNN Only	93.4	0.93	0.92	0.92	0.96
CNN + PCA	94.1	0.94	0.93	0.93	0.97
CNN + PCA + ANFIS	95.8	0.95	0.94	0.94	0.98

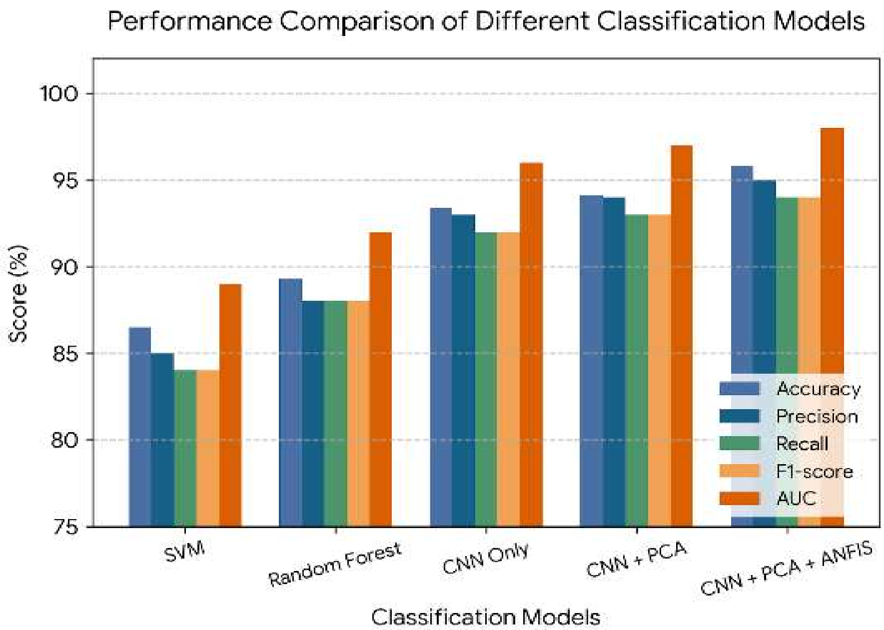

Fig. 3 Comparison of Classification Models

Various models were analysed and compared. The SVM model, Random forest, CNN, CNN and PCA, and CNN+PCAN+ANFIS were compared. The hybrid model CNN, PCA and ANFIS outperformed with greater accuracy.

VI. CONCLUSION

The artificial intelligence based hybridised CNNFIS architecture classifies the histopathological images into normal, dysplasia and oral squamous carcinoma levels. The architecture implements the EfficientNet-B0 for deep feature extraction, and the PCA is used for the reduction of the dimensions. The ANFIS classifier was employed to classify the normal and clear images. The result outcomes reveal that the proposed CNNFIS classifier achieved 95.8%, an average F1-score of 0.94, and an AUC average score of 0.98. The confusion matrix shows the architecture is robust and efficient. The architecture served as a dashboard tool for making the decision for diagnosis of oral cancer.

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