International Journal of Engineering Trends and Technology
ISSN: 2231 – 5381 / https://doi.org/10.14445/22315381/IJETT-V70I4P225
Volume 70 Issue 4, 286-293, April 2022

Original Article

DEEPDAPORCD: Oral Cancer Detection Using Deep Network & Distributed Affinity Propagation

R. Dharani[1], S. Revathy[2]

[1,2] *Faculty of Computer Science and Engineering, Sathyabama Institute of Science and Technology, Chennai, Tamilnadu, India.*

[1]dharani.pit@gmail.com

Received: 11 March 2022 Revised: 18 April 2022 Accepted: 19 April 2022 Published: 26 April 2022

Abstract *- One of the most common cancers is oral cancer. Oral cancer appears to be on the rise all around the world. To separate cancerous lesions from contentious and malignant lesions present in the dental cavity, the doctor must go through a high level. Because there is no pain for the sufferer and they mimic several other lesions, cancer's early stages and eventual manifestations are commonly misunderstood. The research describes a deep learning approach for classifying oral pictures as normal or abnormal. The Distributed Affinity Propagation (AP) algorithm partitioned the diseased patches. Using a deep learning system based on Appearance-based characteristics and Pattern-based features, the segmented cancer spots were further classified as "moderate" or "severe." The deep learning algorithm's key benefit is that it only requires a small number of oral images for the proposed research's categorization and diagnostic phases. Recall Rate, Classification Accuracy, Precision Rate, and Error Rate were used to compare the effectiveness of the presented approaches. The study's findings revealed that a mix of deep learning methods effectively detected oral cancer.*

Keywords *- Affinity Propagation, Appearance-based feature, Cancer Detection, Improved CNN, Medical Image Processing, Oral. Pattern-based features.*

1. Introduction

Oral cancer is among the most frequent malignancies globally, with late detection, a high death rate, and a high incidence. GLOBOCAN forecasts 354,864 cases reported and 177,384 fatalities by 2018 [1]. Two-thirds of the world's cancer rates are found in South Asia's low- and middle-income countries. Oral cancer is caused by tobacco use in any form and excessive alcohol usage. Children's chewing, which commonly involves beans, lime leaves, and occasionally tobacco[3], is one of South and Southeast Asia [2]. Due to their active marketing strategy, these deals are now sold in the sacks market and are popular with the general people. Oral cancer is usually accompanied by delayed diagnosis, particularly in LMICs, with over two-thirds of patients detected late in life, resulting in a terrible survival rate [27]. Cancer treatment, especially in its latter stages, is prohibitively expensive. [28]. A lack of public awareness and education among medical practitioners about oral cancer is one of the key reasons for the slow discovery.

An ulcer known as an oral potentially malignant disorder (OPMD), which must be spotted throughout an initial clinical evaluation from a dental professional, is more likely to start oral cancer (COE). If a concerning lesion is discovered, the patient is directed to a specialist for a condition and treatment. In India, previous research has shown that follow-up leads to lower diagnosis, illness, and death among cigarette and alcohol users [30]. Oral cancer may now be classified with confidence thanks to soft computational approaches. Computers are intelligent devices that employ statistics, optimization, and probabilities to learn from past examples and follow the most difficult models of big, complicated, and quiet data sets. This computer software capability is ideal for medical applications, particularly devices that rely on genetic and complicated parameters. As a result, clever techniques are extensively employed to find cancer prognosis.

The following are the manuscript's significant contributions:

- Oral cancer is diagnosed using CNN classifiers. UCI machine learning archives are used to train CNN classifiers.
- Appearance-based methods and Pattern-based approaches are used to derive features.
- Distributed Affinity Propagation (DAP) is used to isolate areas of oral cancer.
- Contrast Limited Adaptive Histogram Equalization (CLAHE) is used for pre-processing.

This document's manuscript looks like this: The second section looks at some recent research that is pertinent. The proposed method is thoroughly described in Section 3. The experimental results are shown in Section 4, which contains the results of the suggested CNN classification result comparison. Section 5 wraps up with a conclusion.

2. Related Work

Recently, there has been a lot of work done in the literature to classify oral cancer, and this article discusses some of it. Parkin and colleagues are thought to be responsible for 25 cancer cases worldwide. Aziz has submucosal fibrosis, which is an aberrant condition [5]. Zain et al. [6] reported on national epidemiological studies on oral mucosal ulcers. Rosmai et al. [7] pioneered the application of artificial intelligence to identify patients at risk for oral cancer. Kaladhar et al. [8] used a classification algorithm to predict the survival of oral cancer patients. Rosemin and Al [9] established determinants of major success elements in predicting oral cancer susceptibility utilizing ambiguous models, forecasting hospital charges for cancer patients using data-gathering strategies. Kang et al. [10] carried out the research. Sharma and Om [11] described a strategy for early identification and prevention of oral cancer using data collection. Don Chung et al. demonstrated progress in diagnosing oral cancer using optical microscopy. Sincen [13] pioneered the use of a genetic algorithm to diagnose mouth cancer. Chodorowski et al. [14] used real colour imaging to classify mouth ulcers. M. A. Chrisson et al. developed the classification of lip texture into the oral isostatic segment. Neha Sharma et al. [16] examined data extraction approaches to predict oral cancer. Yong Nensun [17] created coloured tumours to detect oral cancer automatically. R.R.Paul et al. [18] demonstrated a unique approach for diagnosing the pathogenic state of her worm-like neural network for oral illness situations.

A hybrid approach combined Fuzzy C-Means and tumour classification algorithms in the oral panoramic image proposed by Alsmadi (2016) [22]. This method provides a significant improvement in the distribution of oral ulcers. Applying a degree of ambiguity to a local group and recognizing the tumour results in inaccuracy. However, the shadow area of the panoramic image will be difficult for false detection because this study relies on the computation of the cluster and the placement of the image borders. Researchers employed machine vector variation (SVM) such as Linear SVM, Quadratic SVM, and Cubic SVM to categorize tumour images using microscopic images. They examined sensitivity, accuracy, and accuracy (Banerjee et al. 2016) [23]. Tanupriya Choudhury et al. (2016) [6] Tanupriya Choudhury et al. Different data extraction strategies were proposed for intelligent categorization of lung and oral malignancies. Linear regression is also performed using logical regression, a powerful modelling method. The ideal number of logical discs is applied and passed valid with automatic attribute selection. Ying Wang et al., Yi - Ying Wang et al., Yi - Ying Wang et al., and Yi - A novel colour approach was introduced for automatically dividing and classifying tumour tissue from microscopic pictures. A three-stage Color Based Feature Extraction (CBFE) system is used. Adjusting the colour normalizes the generated image to the same colour separation. For automatic feature extraction, a selection of computer training templates is used. Zhang et al. (2016) [26] conducted a similar investigation. Using biomass and hybrid algorithms for feature extraction and machine learning. They proposed and evaluated five different tumour classification algorithms. The Ordu Fusion MFS (FSIS) regression system, which incorporates clinical pathology data and autopsy photos, received 93.81 per cent. The entire patient situation was studied in this investigation. The results may not exceed 90% if a collection of medical pathology data or photos is evaluated as a separate model. In other words, the method's accuracy is determined by the patient's information. Galib et al. (2015) [20] studied automated approaches for detecting mouth ulcers. They talked about two technologies for identifying two different forms of ulcers in the mouth. He received 92 per cent good findings in close border lesions with a 32 per cent false-positive rate, while in open border ulcers, he got 85 per cent positive with no false positives. He also highlighted tweaking the algorithm to increase sensitivity to 100% while lowering false positives to 13%. Belvin Thomas and Al proposed classifying and classifying oral cancer lesions into colour images. (2013) [21] utilizing A. N. The goal is to identify a set of reduced features that separate the various groups that produce oral melanoma in various places. The texture and length features of the camera image were recommended. Hobdell et al. (2003) [19] looked into the relationship between socioeconomic position and oral health, hoping to uncover a correlation between socioeconomic and behavioural risk factors and the occurrence of oral cancer and other oral health problems. Their findings explain an oral disease that has been observed in economically advanced countries and that has a clear link between oral cancer and socioeconomic status characteristics.

3. System Methodology

Figure 3.1 depicts the whole workflow of this project. The training technique is depicted in the upper section of the figure. All of the instructive photos of oral cancer and the pertinent cancer kinds are included in the sample database. Then, from cancer's oral region, extract the feature. Finally, the extraction and saving features train the classification model for future use. The bottom of Figure 1 shows the test procedure. The proposed work is divided into 5 steps. They are

1. Noise Removal and Contrast Enhancement
2. Oral Cancer Segmentation
3. Feature Retrieval
4. Cancer Type Categorization

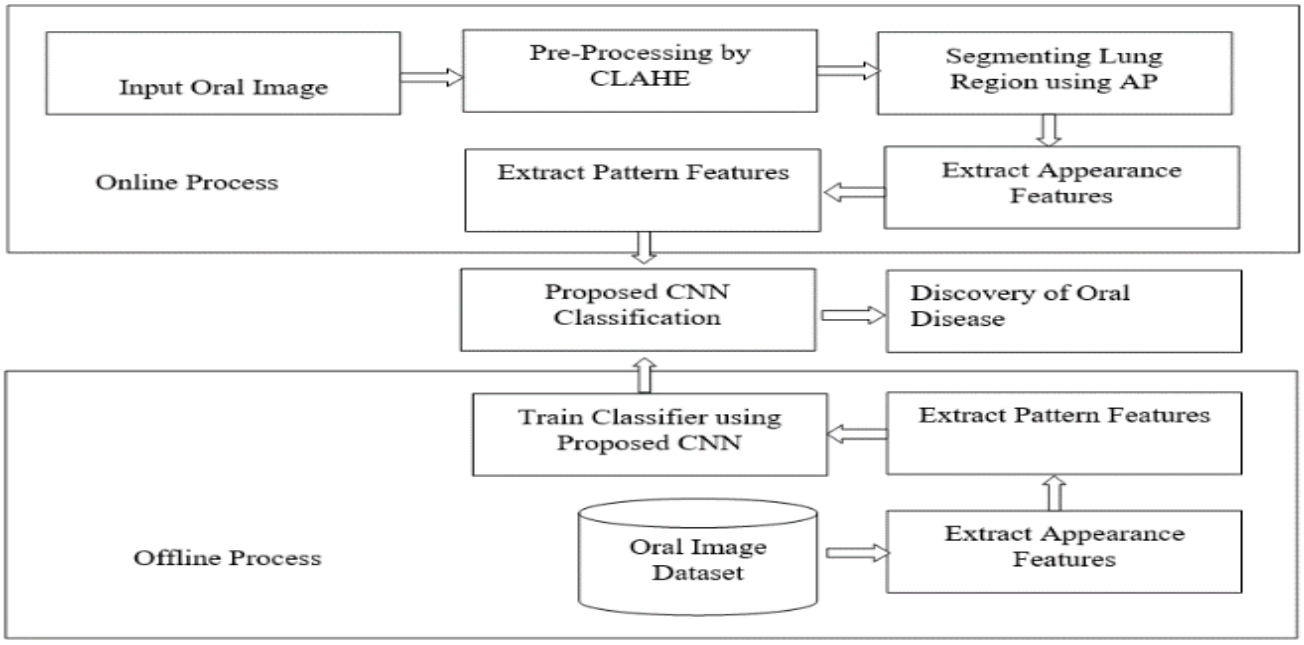


Fig 1. Structural design of the proposed oral cancer detection process

3.1 Noise Removal and Contrast Enhancement

In this step, the input image is denoised and contrast improved. This work uses one algorithm Contrast Limited Adaptive Histogram Equalization (CLAHE), for these two purposes. It is easy to use, uses simple calculations and gives good results in the base area of the image. CLAHE has less noise and can prevent light saturation, which occurs with histogram equalization (HE). There are also some limitations. This method runs too slowly on general-purpose computers, even if it works properly. As improvements occur locally, HE tends to increase noise. The following steps are used to eliminate noise and improve the contrast of the inserted oral image.

1. Get the input image, say X
2. Split the X into four regions, say R1, R2, R3 and R4
3. Repeat the below steps for each pixel in each region
    a. Take the one pixel and consider it as the centre pixel C
    b. Take the pixel in eight directions of C and consider it the neighbour pixel.
    c. And then apply the below formula to detect whether the pixel is affected by noise.

NV = 1 if N_i >= C for i=0,.....7
NV = 0 if N_i < C for i=0,.....7 (1)

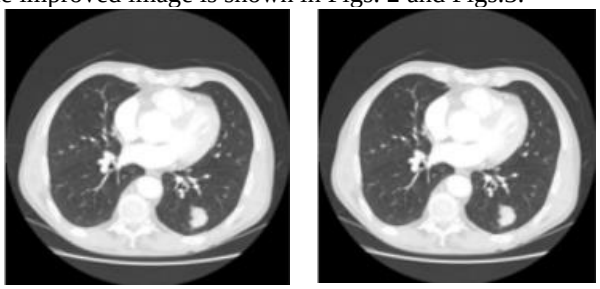
    d. And then calculate the summation of BV for all 8 neighbours to remove noise and improve contrast by using the below formula.

$$\text{CLAHE} = \sum_{i=0}^{7}(BV_i * 2^i) \quad (2)$$

4. Finally, three CLAHE features are produced for CLAHER1, CLAHER2, CLAHER3 and CLAHER4, respectively.
5. Finally, combine these four CLAHE images to produce the final image using the below formula.

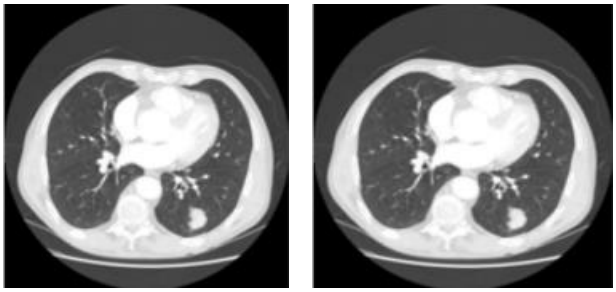
CLAHE = [CLAHER1 CLAHER2 CLAHER3 CLAHER4]

The improved image is shown in Figs. 2 and Figs.3.



(a) (b)

Fig. 2(a) Pre-processed image (b). Oral Image

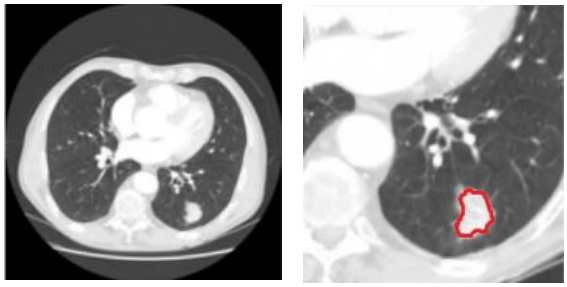


(a) (b)

Fig. 3. (a) Output of CLAHE (b). Resultant Image after Noise Removal

3.2 Oral Cancer Segmentation

This work uses the Distributed Affinity Propagation (AP) to divide cancer-affected pixels from pre-processed images into clusters. First, the pixel collection is divided into several subsets. AP clamps were applied parallel to each subset and formed a set of high-quality specimens. Each example and the subset is merged and grouped one at a time. Then create the end cluster centre. Finally, all images are drawn in parallel cluster centres, and the maximum cluster pattern is the same as the original training model.



(a) (b)

Fig. 4(a). Result of CLAHE 4(b). Result of AP

3.3 Feature Retrieval

This section extracts two types of features from the segmented image. They are Appearance-based features and Pattern-based features.

3.3.1 Appearance-based features

It is measured by detecting the Euclidean distance between reliable samples. The apparent similarity is calculated by Formula 3.

$$V_s(V_i, V_j) = \sqrt{\sum_{i=1}^{n}(q_i - r_i)^2} \quad (3)$$

The apparent similarity of the trustworthy model photos is V_s (V_i, V_j), V_i and q_i. The feature value of the dependable model image is $V_i.r_i$ is the whole quantity of features, and n is the feature value of the trustworthy model picture V_j.

3.3.2 Pattern-based features

It is measured by detecting the Euclidean distance between reliable samples. The pattern similarity is calculated by Formula 4.

$$T_s(C_i, C_j) = \sqrt{\sum_{i=1}^{n}(s_i - t_i)^2} \quad (4)$$

Where $T_s(C_i, C_j)$ is the pattern resemblance between the dependable trial imagery C_i and $C_j.s_i$ are the cancer types of the dependable trial imagery $C_i.t_i$ is the cancer types of the dependable trial imagery C_j and n is the whole amount of cancer types.

3.4 Cancer Type Categorization

This section discusses label assigning to oral cancer images with names based on a novel efficient proposed annotation approach. This novel approach has the following steps.

- Collect Oral Cancer Images and Their Types. And then form the training dataset.
- Extract deep features from all images using the convolution layer of CNN
- Applying Modified Pooling Layer to select the best features
- Oral Cancer Type List Generation.
- Label the test image using Improved CNN Classification

3.4.1 Collect Oral Cancer Images and Their Types

In this step, the oral cancer images are collected from Google on the Web. After collecting the oral cancer images, they form the training dataset with their oral cancer images and put their names as the caption. Denote X= $\{x_1, x_2, x_3, \dots\dots\dots\dots x_n,\}$ as the training dataset. Let C= $\{c_1, c_2, c_3, \dots\dots\dots\dots c_m,\}$ as the image labels corresponding to the training dataset X. This training data set X differs from typical oral cancer recognition data sets because this data set X has several oral cancer images with illumination variation.

3.4.2. Extract deep features from all images using the convolution layer of CNN

In this section, deep features are extracted from all images in the training dataset using the convolution layer of CNN.

3.4.3 Applying Modified Pooling Layer to select best features

After extracting the features, the next step is to select the best features from the convolution layer. This process is done by finding Similarity Matrix Generation using Distance Matrix.

Similarity Matrix Generation using Distance Matrix

To generate the similarity matrix SM1, first, take the mean features of each group MF_j in the training dataset X. To calculate the mean features, first take features set F=$\{f_1, fx_2, f_3, \dots\dots\dots\dots f_n,\}$ of each image x_i in the training dataset X=$\{x_1, x_2, x_3, \dots\dots\dots\dots x_n,\}$ After that form, the feature group FG=$\{f_{11}, fx_{12}, \dots\dots\dots\dots f_{mn},\}$ based on the total no of captions m in the training data set X. Then find mean feature MF_{ij} is calculated by using the below eq.1.

$$MF_{i,j} = \frac{1}{M}\sum_{i=1}^{M}\sum_{j=1}^{N} F_{ij} \quad (5)$$

Where N is the total number of images in the training dataset X. M is the total number of groups in the training dataset X. Then calculate the feature distance value for each image F_i with the mean features of each group MF_{ij} by using the Mahalanobis distance. It is shown in eq.2

$$SM1_{i,j} = \sum_{i=1}^{M}\sum_{j=1}^{N}\left((F_i - MF_{ij})\right)^T C^{-1}(F_i - MF_{ij}) \quad (6)$$

Where N is the total number of images in the training dataset, and M is the total number of groups in the training dataset. F_i is the feature of the ith image in the training dataset. MF_{ij} is the mean feature value of the ith image and jth group in the dataset. C^{-1} is the inverse covariance matrix of the feature value, and T is the transpose of the value.

3.4.4. Oral Cancer Type Suggestion List Generation

In this step, the suggestion list SNL_i for each image x_i in the training dataset X is created using the similarity matrix SM. The suggestion label SNL_i for each image x_i is produced by sorting the distance value of all groups in ascending order. It is shown in the eq10.

$$SNLV_i = \text{sort}\left(SM_{i,1}, SM_{i,2}, SM_{i,3,} \dots\dots\dots\dots, SM_{i,N}\right) \quad (7)$$

$SM_{i,1}$ is the similarity rate of the ith image 1st group, and N is the total number of groups in the training dataset. After finding the shortest distance value $SNLV_i$ value in ascending order for each image x_i, create the suggestion SNL_i by combining the image label C_i for each image x_i based on $SNLV_i$. The total number of suggestion names σ is taken to create a suggestion list in the range of 10 to 50. To find the best value of σ, separate experiments are conducted in the result and analysis section. Based on σ, the suggestion list SNL_i for each image x_i is calculated using below eq 11.

$$SNL_i = \{find(SNLV_1 == C) \cup find(SNLV_2 == C) \dots\dots\dots \cup find(SNLV_\sigma == C)\}\} \quad (8)$$

3.4.5. Label the test image using Improved CNN Classification

This step label the given test oral cancer image with types. The improved CNN approach uses two conditions to label the oral cancer image. The conditions are explained below in a detailed manner.

- Apply improved CNN to classify oral cancer images. If the result is the known class, we label oral cancer images with types associated with the known class.
- If the result is the unknown class, use the suggestion list to recommend a type list for oral cancer images. To do this, the below steps are followed
  - Compute the similarity of the input test oral cancer image with the all image in the training dataset image to find the closest image.
- And then take the recommend a type list from the suggestion list based on the closest image which is getting from the similarity calculation.

4. Results and Evaluation

4.1 Data Collection

To assess the effectiveness of the proposed CNN, the UCI data set for direct CT scans were used. There are also different classifications for mouth cancer. The UCI dataset is the largest cancer screening library available to the public, including 1018 CT scans of the mouth cavity. Oral cancer can be observed on a CT scan in various locations. Figure 5 illustrates an oral CT scan.

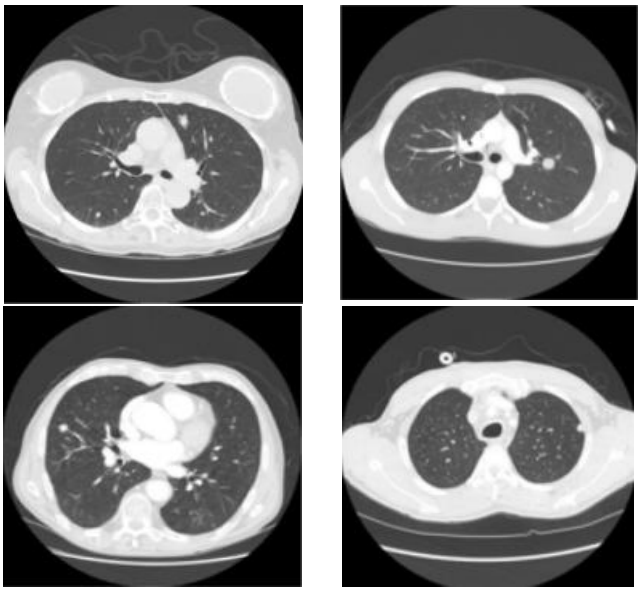


Fig. 5 Few Samples Images Data Set

4.2 Performance Metrics used

Sensitivity (Sn)

It was determined using the following formula (9)

$$Sn = \frac{T_r P}{T_r P + F_a N} \quad (9)$$

Specificity (Sp)

This metric was determined through the following formula (10),

$$Sp = \frac{T_r n}{T_r n + F_a p} \quad (10)$$

Classification Accuracy (CA)

It was determined using the following formula(11)

$$CA = \frac{T_r P + T_r n}{T_r P + T_r n + F_a p + F_a N} \quad (11)$$

Error Rate (ER)

This metric was determined through the following formula(12)

$$Error\ Rate = \frac{Number\ of\ images\ categorized\ incorrectly}{Total\ number\ of\ images} \quad (12)$$

4.3 Analysis of Experiments

4.3.1 Techniques for Feature Derivation Analysis

To assess the success of this feature deviator, it is compared to other ways using the metrics listed in section 4.2, and the results are shown in Table 1.

Table 1. Result of Proposed Feature Deviators

Data Set				
Feature Derivates				
Parameters	CA	Sn	Sp	ER
Wavelet	85.79	94.61	97.12	14.21
CVH	84.33	93.72	96.06	15.67
Zernike	85.92	93.03	97.01	14.08
Appearance + Pattern	94.82	95.661	95.531	5.18

The outcome of Table 1 is also shown in the picture formation below figure.

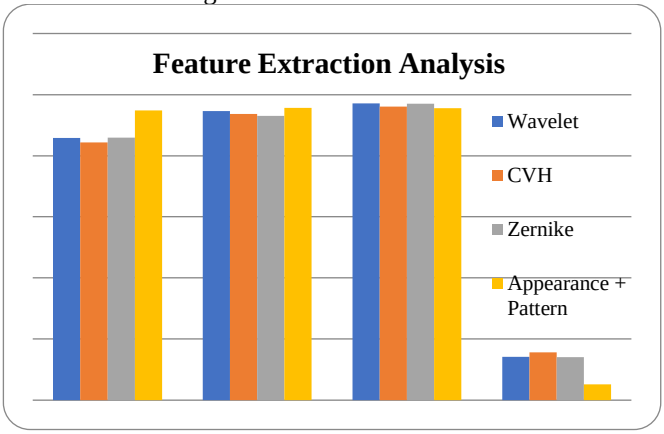


Table 1 shows that the proposed features have the highest Sn of 95.661, and they are more potent than other technologies because they have the highest cost.

4.3.2 Examining Oral Cancer Partitioning Techniques

To assess the effectiveness of this cancer partition method, it is compared to other ways using the metrics listed in section 4.2, and the results are shown in Table 2.

Table 2. Result of Proposed Oral Cancer Partition Scheme

Data Set				
Partitioning Methods				
Constraints	CA	Sn	Sp	ER
FCM	86.731	87.571	87.441	13.269
K-Means	85.251	86.111	85.981	14.749
ABC	93.251	94.061	93.931	6.749
AP	96.471	97.281	97.151	3.529

The outcome of Table 2 is also shown in the picture formation in the below figure.

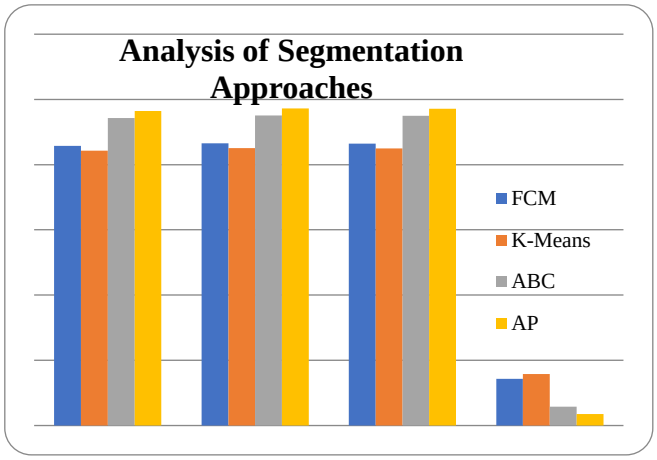


Table 2 reveals that AP had the highest Sn, 97.281, and was more potent than other technologies because it had the highest cost.

4.3.3 Methodologies for Classification of Oral Cancer

The results of comparing this cancer classification approach to other methods utilizing the metrics given in section 4.2 are shown in Table 3.

Table 3. Result of Proposed Oral Cancer Classification Approaches

Data Set				
Classification				
Constraints	CA	Sn	Sp	ER
SVM	94.25	95.63	94.93	5.75
Bagging	89.28	90.77	89.97	10.72
Naive Bayes	85.73	87.65	87.44	13.27
KNN	85.25	86.23	85.98	14.75
AdaBoost	92.78	93.84	91.45	7.2
IELM	96.16	97.41	96.89	3.84
CNN	98.22	98.47	98.8	1.78
Proposed CNN	98.26	98.51	98.84	1.74

The outcome of Table 3 is also shown in the picture formation below figure.

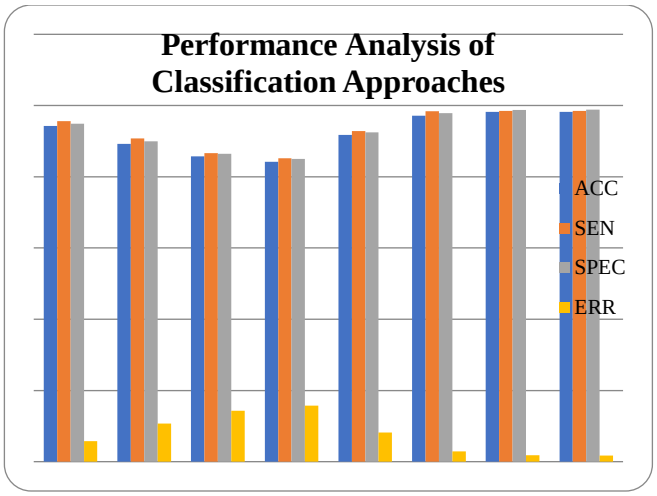


Table 3 demonstrates that the suggested CNN has the highest Sn, 98.49, and is more potent than other technologies because it has the highest cost.

5. Conclusion

The stage is an important task for the oncologist when diagnosing oral cancer. Therefore, it is important to differentiate between different stages of oral cancer to ensure the effective treatment of cancer patients. Data conversion is performed to standardize the data, and the features are derived using appearance and pattern. Improved CNN was used to classify the extracted features. Improved CNN can attain a 98.24 per cent average accuracy. As a result, the findings indicate that the suggested CNN approach is quite effective in detecting oral cancer. These findings show that other approaches are better at representing the intended CNN. In addition, similar tests were carried out on the classification approach. The results show that AP performs best in the classification step due to the higher value of detection accuracy than other methods.

References

[1] F. Bray, J. Ferlay, I. Soerjomataram, R. L. Siegel, L. A. Torre, and A. Jemal, Global Cancer Statistics 2018: GLOBOCAN Estimates of Incidence and Mortality Worldwide for 36 Cancers in 185 Countries, CA: A Cancer J. Clinicians, 68(6) (2018) 394–424.
[2] H. Gelband, P. Jha, R. Sankaranarayanan, and S. Horton, Disease Control Priorities: Cancer, Washington, DC, USA: World Bank, 3 (2015).
[3] J. Rimal, A. Shrestha, I. K. Maharjan, S. Shrestha, and P. Shah, .Risk Assessment of Smokeless Tobacco Among Oral Precancer and Cancer Patients in the Eastern Developmental Region of Nepal,. Asian Pacific J. Cancer Prevention, 20(2) (2019) 411–415.
[4] D. M. Parkin, P. Pisani, J. Ferlay, Estimates of the Worldwide Incidence of Twenty-Five Major Cancers in 1990. Int J Cancer, 80 (1999) 827–41.
[5] S. R. Aziz, Oral Submucous Fibrosis: An Unusual Disease, J N J Dent Assoc, 68 (1997) 17–19.
[6] R. B. Zain, N. Ikeda, I. A. Razak, A National Epidemiological Survey of Oral Mucosal Lesions in Malaysia, Community Dent Oral Epidemiol, 25 (1997) 377–83.
[7] M. D. Rosmai, A. K. Sameemii, A. Basir, I. S. Mazlipahiv, M. D. Norzaidi, The use of Artificial Intelligence to Identify People at Risk of Oral Cancer: Empirical Evidence in Malaysian University, International Journal of Scientific Research in Education, 3(1) (2010) 10-20.
[8] DSVGK. Kaladhar, B. Chandana, P.B. Kumar, Predicting Cancer Survivability Using Classification Algorithms, International Journal of Research and Reviews in Computer Science, 2(2) (2011) 340–343.
[9] M. D. Rosmai, A. Basir, S. A. Kareem, S. M. Ismail, M. D. Norzaidi, Determining the Critical Success Factors of Oral Cancer Susceptibility Prediction in Malaysia Using Fuzzy Models, Sains Malaysiana, 41(5) (2012) 633–640.
[10] J. O. Kang, S. H. Chung, Y. M. Suh, Prediction of Hospital Charges for Cancer Patients With Data Mining Technique, J Kor Soc Med Informatics, 15(1) (2009) 13-23.
[11] N. Sharma, H. Om, Framework for Early Detection and Prevention of Oral Cancer Using Data Mining, International Journal of Advances in Engineering and Technology, 4(2) (2012) 302-310.
[12] Woonggyu Jung, Jun Zhang, Jungrae Chung, Petra Wilder–Smith, Matt Brenner, J. Stuart Nelson and Zhongping Chen, Advances in Oral Cancer Detection Using Optical Coherence Tomography, IEEE Journal of Selected Topics in Quantum Electronics, 11(4) (2005) 811 – 817.
[13] Simon Kent, Diagnosis of Oral Cancer Using Genetic Programming – A Technical Report, CSTR -96-14.
[14] A. Chodorowski, U. Mattsson, T. Gustavsson, Oral Lesion Classification Using True Color Images, Proceedings of SPIE, ISBN. 978081943132, 3661 (1999) 1127 – 1138.
[15] M. Muthu Rama Krishnan, Chandran Chakraborthy, Ajoy Kumar Ray, Wavelet Based Texture Classification of Oral Histopathological Sections, International Journal of Microscopy, Science, Technology, Applications and Education, 897-906.
[16] Neha Sharma, Nigdi Pradhikaran, Akurdi, Comparing the Performance of Data Mining Techniques for Oral Cancer Prediction, Proceedings of the 2011 International Conference on Communication, Computing & Security (ICCCS'11), ISBN: 978-1-4503-0464-1, New York, USA, (2011).
[17] Yung –Nien Sun, Yi-Ying Wang, Shao-Chien Chang, Li-Wha Wu and Sen – Tien Tsai, Color – Based Tumor Segmentation for the Automated Estimation of Oral Cancer Parameters, Microscopy Research and Technique, 73(1) (2010) 5- 13.
[18] Hobdell MH, Oliveria ER, Bautista R, Myburgh NG, Lalloo R, Et Al. Oral Diseases and Socio economic socio economic Status (SES). Br Dent J. 194(2) (2003) 91-96.
[19] Galib, S., F. Islam, M. Abir & H.K. Lee. Computer Aided Detection of Oral Lesions on CT Images, Journal of Instrumentation, 10(12) (2015).
[20] Belvin Thomas, Vinod Kumar, Sunil Saini. Texture Analysis Based Segmentation and Classification of Oral Cancer Lesions in Color Images Using ANN, IEEE International Conference on Signal Processing Computing and Control (ISPCC) , (2013) 1-5.
[21] Alsmadi, M.K.A Hybrid Fuzzy C-Means and Neutrosophic for Jaw Lesions Segmentation, [Press Release], Retrieved From Https://Doi.Org/10.1016/J. Asej.2016.03.016.(2016).
[22] Banerjee, S., Chatterjee, S., Anura, A., Chakrabarty, J., Pal, M., Ghosh, B., Chatterjee, J. Global Spectral and Local Molecular Connects for Optical Coherence Tomography Features To Classify Oral Lesions Towards Unravelling Quantitative Imaging Biomarkers, RSC Advances. 6(9) (2016) 7511-7520.
[23] Tanupriya Choudhury, Vivek Kumar, Darshika Nigam, Bhaskar Mandal. Intelligent Classification of Lung Oral Cancer Through Diverse Data Mining Algorithms, International Conference on Microelectronics and Telecommunication Engineering. (2016).
[24] Yi-Ying Wang, Shao-Chien Chang, Li-Wha Wu, Sentien Tsai and Yung-Nien Sun. A Color-Based Approach for Automated Segmentation in Tumor Tissue Classification, Conference of the IEEE EMBS Citéinternationale, Lyon, France. (2016).

[25] Chang, S.W., Abdul-Kareem, S., Merican, AF, Zain, RB Oral Cancer Prognosis Based on Clinicopathologic and Genomic Markers Using A Hybrid of Feature Selection and Machine Learning Method, BMC Bioinformatics, 14(1) (2016)
[26] J. G. Doss, W. M. Thomson, B. K. Drummond, and R. J. R. Latifah, Validity of the FACT-H&N (V 4.0) Among Malaysian Oral Cancer Patients,'' Oral Oncol., 47(7) (2011) 648–652.
[27] H. Amarasinghe, R. D. Jayasinghe, D. Dharmagunawardene, M. Attygalla, P. A. Scuffham, N. Johnson, and S. Kularatna, 'Economic Burden of Managing Oral Cancer Patients in Sri Lanka: A Cross-Sectional Hospital-Based Costing Study, BMJ Open, 9(7) (2019).Art. No. E027661.
[28] R. D. Jayasinghe, L. P. G. Sherminie, H. Amarasinghe, and M. A. Sitheeque, Level of Awareness of Oral Cancer and Oral Potentially Malignant Disorders Among Medical and Dental Undergraduates, Ceylon Med. J., 61(2) (2016) 77.
[29] O. Kujan, A.-M. Glenny, R. Oliver, N. Thakker, and P. Sloan, Screening Programmes for the Early Detection and Prevention of Oral Cancer, Austral. Dental J., 54(2) (2009) 170–172.