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A study on Medical Imaging Modalities and Artificial Intelligence methods for Identification of Oral Cancer

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Abstract - All disorders that result in abnormal and uncontrolled cell division and development are collectively referred to as cancers. One of the more prevalent cancer types identified throughout the global community is oral cancer. A variety of modifiable risk factors, including sugar consumption, tobacco use, alcohol use, poor hygiene, and their underlying societal and economic determinants, contribute to the development of oral cancer. These risk factors are also similar to many non-communicable diseases (NCDs). Due to infection with the human papilloma virus, 16, (HPV 16), it's also a novel factor for causing oral cancer without any tobacco association. Oral cancer, also known as oral squamous cell carcinoma (OSCC), is an ulceroproliferative oral mucosa lesion that can impact any mouth part, from the lips to the oropharynx. For the management of OSCC, variants in the composition of patients, clinical paradigms, and technological advances offer both opportunities and challenges. Imaging remains an increasingly significant component in the staging, planning, and monitoring of patients with OSCC. Molecular and cellular changes in cells can now be detected non-invasively using imaging methods. The Artificial Intelligence approaches are also being utilized to enhance their incorporation into routine therapeutic operations. This study primarily focused on AI aspects of oral cancer identification. It provides a comprehensive overview of the existing imaging modalities, prominent AI models for identification, their performance, and their limitations. In the current review, we summarize the current progress of machine learning, deep learning, and transfer learning in OSCC detection, with a particular focus on methods of classification.

Keywords: *Cancer, oral cancer, squamous cell carcinoma, risk factor, medical imaging*

I. Introduction

Significant research has been conducted to enhance machine intelligence during the Industrial Revolution era in which we currently live. This technology enables computers to learn from their mistakes and understand the world through a hierarchy of concepts. Pattern recognition provides an essential tool for activities involving healthcare analytics [1][2]. Oral cancer may display several behavioral traits. For the treatment of oral cancer to be appropriate and effective, early detection and accurate prognostic prognosis are essential. The models of machine learning and deep learning have received recognition for their potential to transform the treatment of cancer by improving diagnostic precision and prognostication. When a tumor appears in a portion of the mouth, it is called oral cancer. It could be on the tongue's surface, the inside of the cheeks, the palate, the lips, or the gums. Additionally, tumors can form in the salivary glands, tonsils at the back of the mouth, and pharynx, the portion of the throat that connects the mouth to the windpipe. Understanding the type of oral cancer will aid in performing an accurate diagnosis and therapy. Oral cancer is characterized by unchecked cell development that over time invades and affects the neighboring organs. Smoking, chewing tobacco, drinking alcohol excessively, being infected with HPV, and exposure to the sun are all risk factors for oral cancer.

Head and neck cancer can also have the following forms: [3] laryngeal cancer, which affects the voice box. Nasopharyngeal cancer, affects the

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region behind the nose that makes up the pharynx. Oropharyngeal cancer, affects the area of the throat that is immediately behind the mouth. Cancer of the thyroid gland, a butterfly-shaped gland on either side of the windpipe. Cancer of the hypopharynx, the area of the throat directly behind the larynx.

Squamous cell carcinomas, commonly known as squamous cell cancers, make up the majority of oral cancers. Squamous cells, which are thin, flat cells that make up the lining of the mouth and throat, are where these malignancies begin[4]. It's crucial to get an early diagnosis[5] to prevent oral cancer. People who seem healthy and are not suspected of having oral cancer are routinely given screening exams.

The incidence of Oral Squamous Cell Carcinoma is 3% in the United States of America whereas it is 30% in India and other Asian countries [6]. According to the American Cancer Society, approximately 48,000 Americans develop oral cancer every year and 8500 people die of the disease annually. India records more than 1,00,000 cases of oral cavity cancers every year. India has the highest prevalence of oral cancer in the world (19/100, 000 population). It is the most common cancer in men and the third most common cancer in women and constitutes 13%–16% of all cancers. Of all the oral cancers, 95% are related to the use of tobacco products. By finding oral cancer before any symptoms appear, screening lowers mortality.

A diagnostic test is required to determine if the patient has cancer or not and if the screening test result is abnormal. It is possible to suspect oral cancer by using screening methods like magnetic resonance imaging (MRI), computerized tomography (CT), positron emission tomography (PET), and histology.

II. REVIEW OF LITERATURE

A study is currently being conducted on the literature regarding Artificial Intelligence-based research applications in oral cancer. The aim is to identify cutting-edge algorithms along with their advantages and disadvantages. To gather information, three databases were searched: Google Scholar, PubMed, and Scopus. Publications were examined using the following search keywords: "oral cancer," "Machine Learning," "Identification," "Deep Learning," and "Artificial Intelligence." Additional research was carried out based on the reference lists of selected papers and relevant reviews. Out of the 50 publications reviewed, 40 studies met the inclusion criteria for this review. Eight studies were disqualified for various reasons, including reliance on traditional statistical techniques, resulting in a final total of 41 relevant studies. All 41 were thoroughly investigated and analyzed, providing insights into the role of AI in screening, early diagnosis, prediction, and management of oral squamous cell carcinoma.

In this review, identified nine different types of visual modalities. Among these, positron emission tomography (PET) and Pap smear images were the least commonly utilized, whereas histopathology images were the most frequently employed. A significant number of researchers have also utilized hyperspectral and multispectral images for detecting oral cancer. Additionally, some studies have incorporated endoscopy images, particularly endomicroscopy, which produces high-resolution, histology-like visuals. Computed tomography (CT) images, including T1, T2-weighted, and contrast-enhanced CT images, have also been widely used for classification purposes. Furthermore, researchers have applied magnetic resonance imaging (MRI) to categorize oral anomalies. Details regarding the types of images and the volume of publications that have utilized these modalities are summarized in Table 2.1. Table 2.2 provides information drawn from each of the included studies.

Table 2.1 Types of Image Modalities

Imaging Modality	Number of Articles	Reference	Imaging Technique
Autofluorescence Image	5	[7-11]	An image format is created by capturing the inherent fluorescence of biological components using a specialized ophthalmoscope scanner.
PAP Smear	1	[12]	A camera-equipped microscope is used to take PAP smear images.
Raman Spectral Images	5	[13-17]	Raman spectroscopy is a method that uses laser light scattering measurements to offer molecular details about a material. It can be carried out utilizing fiber-optic probes directly on living tissue (in vivo) or on removed tissue samples (in vitro).
MRI	2	[18,19]	Strong magnetic fields and radio waves are used in magnetic resonance imaging, or MRI, to provide finely detailed images of the body's internal components. In some cases, it can be helpful for determining the disease's stage and extent.
Photographic	3	[20-22]	Digital photos are typically captured with a digital point-and- shoot camera or a smartphone camera. It records pictures with hues and wavelengths that are comparable to those seen by the human eye within the visible spectrum of light.
CT	7	[23-29]	When evaluating oral cancer, a CT (computed tomography) scan is a useful imaging method. It offers thorough cross-sectional pictures of the surrounding structures and the oral cavity.
Radiograph	2	[30-31]	like X-rays, which are utilized as a supplemental diagnostic method to assess oral cancer.
Histopathology	13	[32-44]	A picture from histopathology displays the tissues' microscopic characteristics. Biopsy samples are examined in order to produce these images.
Endomicroscopy	1	[45]	Using this imaging method, tissues at the cellular level can be seen in real time at a microscopic level. It offers fine-grained pictures of the cellular characteristics and tissue architecture.

Table 2.2 A List of Articles for Oral Cancer Identification

Author	Image Type	Prominent Algorithm	Dataset	No.of Samples	Findings & Future
Wang et al., 2003 [7] China	Autofluorescence	partial leastsquares and artificial neural network (PLS-ANN)	Department of Oral and Maxillofacial Surgery, National Taiwan University Hospital	97	-To increase the number of samples - leave-one-out cross-validation might result in over optimistis
Majumder et al., 2005 [8] India	Autofluorescence	recursive feature elimination (RFE) in Support Vector Machine	Government Cancer Hospital, Indore	408	-To perform cross validation
Nayak et al., 2006 [9] India	Autofluorescence	principal component analysis (PCA) and artificial neural network (ANN)	College of Dental Surgery and Sai Baba Cancer Hospital, Manipal Academy of HigherEducation	143	-simulation will reproduce correctly only spectra from normal samples and will reproduce only part of the spectrum for other samples
Awais et al., 2020 [10] China	Autofluorescence	linear discriminant analysis and k-nearest neighbor (LDA-KNN)	Oral Cancer Research Co-ordination Centre, University of Malaya	24	-aim to reconstruct the GLCM co-occurrence matrix n other directions such as 45, 90 and 135 degree.
Chan et al., 2019 [11] Taiwan	Autofluorescence	FCN	Oral Medicine, College of Medicine and Hospital	80	-The omission of the segmentation branch results in a poor IOU performance
Chatterjee et al., 2018[12] India	PAP Smear	SVN,KNN, Random Forest	Dept. Maxillofacial Surgery at Guru Nanak Institute of Dental Sciences	60	-Suggest to increase the augmentation feature to distinguish classification model
Mingxin et al., 2019[13] China	Raman spectroscopy	ConvNets classifier	Peking Union Medical College Hospital.	24	-To model nonlinear effects and encodes information about variations in intensities at specific bands
Jeng et al., 2019 [14] Taiwan	Raman spectroscopy	Linear discriminant analysis and principal component analysis	Chang Gung Memorial Hospital	80	- to target a maximum number of samples for each sub-site - to use meta-learning and neural networks approaches
Du et al., [15]2013 China	Raman spectroscopy	Gaussian Process	School and Hospital of Stomatology, Wuhan University	852	-To apply the application prospect of this method in other similar diseases
Jeyaraj et al.,2019[16] India	Hyperspectral	Deep CNN	Emory Molecular and	100	-To prove by Fusing base classifier

			Translational Imaging Center		
Kiruthika et al., [17] 2021 India	Hyperspectral	Restricted Boltzmann Machines	Not Described	Not Given	-
Jiliang et al., 2020 [18]	MRI	LR, RF , ANN, synthetic minority oversampling technique (SMOTE)	Shanghai Ninth People's Hospital (Shanghai, China)	80	-To explore more ML techniques and sub-sampling methods
Yuan et al., 2021 [19] China	MRI	LR, RF, NB,SVM, AdaBoost, and NN	Shanghai Ninth People's Hospital (Shanghai, China)	116	- need multicenter prospective study, featuring external validation
Marzouk et al., [20]2022 Saudi Arabia	Photographic images	DenseNet, Autoencoder	Kaggle repository	131	-advanced DL models can be used for the classification of medical images to diagnose oral cancer
Alanazi et al., [21] 2022 Saudi Arabia	Photographic images	Deep Belief Network	Kaggle repository	1100	- advanced DL models can be utilized as a classifier to optimize the detection performance.
Nandhitha et al., [22] 2022 India	Photographic images	CNN	Internet	1200	to gather more images -to implement semantic segmentation for selecting lesion region from an input image
Xu et al., [23] China	CT	3DCNN	Shanghai Ninth People's Hospital (Shanghai, China)	7000	-To combine different imaging modalities
Galib et al., [24] 2015 USA	CT	MLP	Vatech Co., Ltd, South Korea	52	- To detect lesions in maxilla - To improve detection accuracy for lesions with unclear appearances.
Dharani et al., [25] 2021 India	CT	CNN	UCI Machine Learning Repository	1018	- To work with real time data set
Yang et al., [26] 2023 China	CT	CNN, SVM	Tianjin Stomatology Hospital, China	13799	-To explore with different OCT systems using deep learning methods.

Prabakaran et al., [27] India	CT	CNN, SVM, Naïve Bayes	Kaggle	100	To compare with many classifers
Hu et al., 2018 [28] Australia	CT	SVM	The Cancer Imaging Archive	600	-To find efficient algorithm to improve accuracy - To detect tumors in the edge area and small tumors in the early stages
Ali et al., [29] 2019 India	CT	SVM	National Cancer Website	-	- to work with Convolution Neural Network
Nurtanio et al, [30] 2013 Indonesia	Dental Radiograph	SVM	Oral Radiology	133	to increase the accuracy of GLCM texture features.
Anuradha et al., [31] 2018 India	Dental Radiograph	Fuzzy Cognitive Map	Department of Radiology, Mid-Michigan Medical Center, Michigan	50	Increase the number of GLCM features, to avoid over – segmentation
Krishnan et al., [32] 2012 India	Histopathology	Bayesian, SVM	Depa rtment of Oral and Maxillo facial Pathol ogy, Guru Nana k Institu te of Dental Sciences and Research, Kolkata ,	119	-requires for specially automated diagnosis.
Kripa et al., [33] 2019 India	Histopathology	Feed forward Network	To classify the image as normal or cancer	25	-Usage of neural network is not appropriate because having many complex equations
Panigrahi et al., [34] 2020India	Histopathology	Capsule Network	GDC Portal	500	can be extended to classify the different stages of oral cancer
Rahman et al., [35] 2020 India	Histopathology	SVM,LR, kNN, Linear discriminant, Decision tree	Dr. B. Borooah Cancer Institute, Ayursundra Healthcare Pvt. Ltd	452	-
Amin et al., [36] 2021 Pakistan	Histopathology	VGG16, InceptionV3, and Resnet50	To identify cancerous images than normal	1224	-aim to generate large datasets, to consider different cross validation methods
Musulin et al., [37] 2021 Croatia	Histopathology	Xception	Clinical Dept of Pathology and Cytology, Clinical Hospital Center, Rijeka	2056	-To increase the number of images, to create predictive algorithms for prognostic indicators

Rahman et al., [38] 2022	Histopathology	AlexNet	Kaggle	4946	- extended to fuse datasets - apply fuzzy techniques to get more results empowered with federated machine learning
Gupta et al., 2022 [39] India	Histopathology	SVM, KNN, Naïve Bayes and Boosted trees	Govt. Dental College and Hospital, Jammu, India.	10,496	to classify multi-modality medical images like MRI and CT scans, to explore Feature fusion and feature attention
Deo et al., 2022 [40] India	Histopathology	ResNet+EWT	Kaggle	695	to incorporate other pre-trained deep-learning models
Fati et al., [41] 2022 Saudi Arabia	Histopathology	ANN + Hybrid features	Kaggle	5192	-to propose on more than one data set -integration of feature extraction from more than one CNN model
Deif et al., [42]	Histopathology	XGBoost	Kaggle	1224	-
Panigrahi et al., [43] 2023India	Histopathology	Baseline CNN	Institute of Dental Sciences (IDS), SUM Hospital, Bhubaneswar	4000	- To consider Very deep neural network ResNet150, EfficientNet (200 to 800 layers)
Anantha Krishnan et al [44] 2023	Histopathology	VGNet, Random Forest	Dr. B. Borooah Cancer Institute and Ayursundra Healthcare	1224	-To work with different dataset samples from different centers -To Compare the models against human experts in the field
Aubreville et al., [45] 2017 Germany	Confocal Laserendo microscopy	CNN	Department of Oral and Maxillofacial Surgery (University Hospital Erlangen	116 Video Sequence	- transfer the fndings to further entities of squamous cell carcinomas in the upper aero-digestive tract.

Consequently, the results in this table highlight the significance of artificial intelligence—specifically, machine learning and deep learning algorithms—in the processing of medical images for the purpose of predicting oral cancer using a variety of medical images.

Drawing conclusions from the complete literature review, the following findings are made:

(i) Studies on the early identification of oral cancer will be greatly altered by artificial intelligence, which will enhance clinical practice in general. Artificial intelligence offers great potential for task automation through the recognition of intricate patterns.

(ii) Careful data preparation, feature selection, model training, and rigorous validation using relevant datasets are necessary for the effective application of artificial intelligence technologies for the detection of oral cancer.

III DISCUSSION

The model's validation procedure is quantitatively assessed using precision, sensitivity, specificity, and accuracy to identify oral tissues across statistical measures. The number of testing samples that are correctly identified as positive in all samples with the ground truth positive is reflected in the sensitivity of a classifier. Another name for it is true positive rate (TPR). The number of testing samples that are correctly categorized as negative in all samples where the ground truth is negative is the expression used to describe specificity. Another name for it is true negative rate (TNR). The precision, also known as positive predictive value, measures the percentage of correctly classified positive photos relative to all positive anticipated images. The quantity of testing samples in the whole testing set that are accurately identified is known as accuracy. The model's validation process's quantitative evaluation is eIt indicates that the model correctly forecasts the patient's state (positive or negative). Through training the model on a fraction of input data and testing it on a subset of input data that hasn't been seen before, cross-validation[27] is a strategy for validating the model's efficiency. Using the K-fold cross-validation method, the input dataset is split up into K groups of equal-sized samples. Folds are the term for these samples.

$$\textbf{Sensitivity} = \frac{TP}{TP+FN} * 100\%$$

$$\textbf{Specificity} = \frac{TN}{TN+FP} * 100\%$$

$$\textbf{Precision} = \frac{TP}{TP+FP} * 100\%$$

$$\textbf{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} * 100\%$$

True Negative(TN): Model has given prediction No, and the real or actual value was also No. **True Positive(TP):** The model has predicted yes, and the actual value was also true. **False Negative(FN):** The model has predicted no, but the actual value was Yes. **False Positive(FP):** The model has predicted Yes, but the actual value was No.

3.1 Summary of Machine Learning Models

The results of the literature review have identified three distinct approaches to artificial intelligence that have been employed in earlier research: machine learning, deep learning, and transfer learning. Table 3.1 and Figure 3.1 make it clear which machine learning method is most often used to classify oral carcinoma cells. It has been used to help in the diagnosis and categorization of oral cancer. These algorithms make use of patterns and features that have been taken from different medical imaging data sources. In this field, machine learning techniques including SVM, Random Forest, ANN, Decision Tree, and Gradient Boosting are frequently employed. When it comes to medical image analysis, feature extraction techniques entail taking pertinent features out of the images and use them as machine learning input.

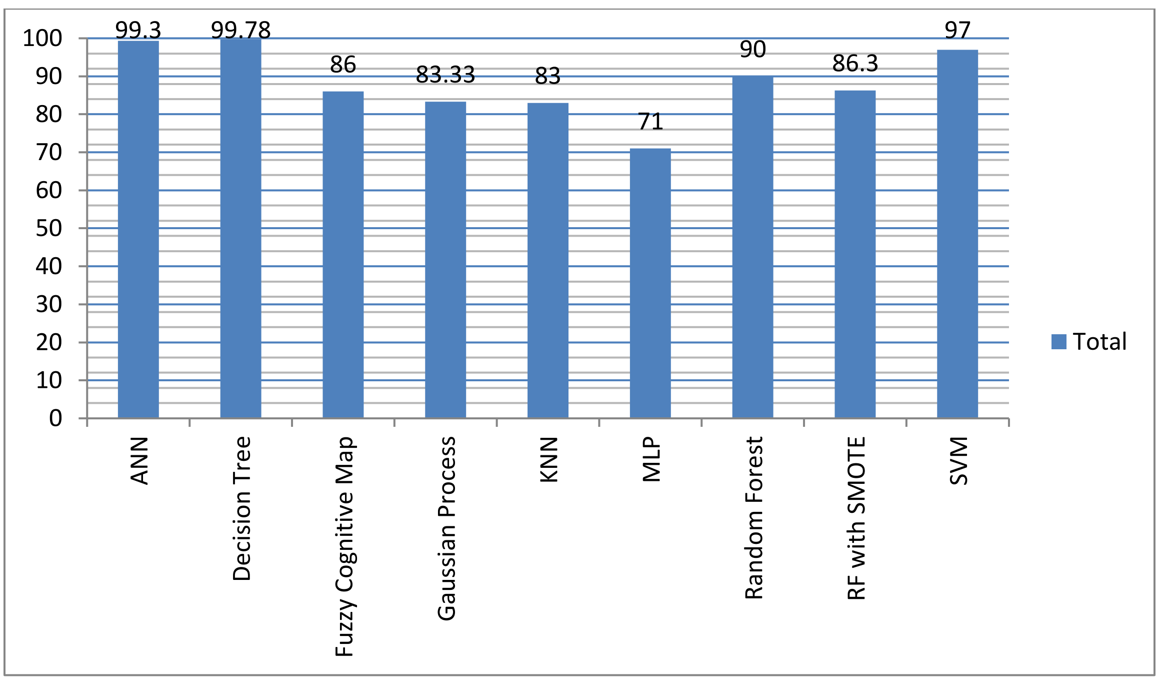
Based on the intensity values of the pixels, Intensity Features are calculated. Add features based on a histogram, skewness, mean, and standard deviation. Texture features: depict the patterns and spatial configurations of pixel intensities. wavelet transform, local binary patterns (LBP), gray-level co-occurrence matrix (GLCM), or gray-level run length matrix (GLRLM). Shape Features: describe a structure or region's geometrical characteristics. Incorporate characteristics like compactness, circularity, eccentricity, area, and perimeter. Identify borders and contours of structures in medical information by using edge and contour features. Both contour tracing techniques and edge detection algorithms can be used to compute them. Wavelet Transform: This technique can be used to extract both spatial and frequency information from medical images.

The results also show that, in comparison to the other methods, the decision tree-based categorization method produced results with a better degree of accuracy. The results show that the SVM technique was able to detect the cell under test in the various datasets with a greater accuracy of over 99%, as demonstrated in Figure 3.1.

Table 3.1 shows the performance metrics based on ML.

Ref	Classification Model	Sensitivity	Specificity	Precision	Accuracy	Validation
[7]	ANN	81	96	88	86	leave-one-out
[8]	SVM	93	95	-	85	leave-one-out
[9]	ANN	96.5	100	-	98.3	Hold out
[10]	KNN	85	84	-	83	5-FOLD
[12]	Random Forest	-	-	-	90	Hold out
[14]	SVM	90.90	83.33	-	87.5	k-fold, leave-one-out-cross-validation
[15]	Gaussian Process	80	100	-	83.33	Hold out
[18]	RF with SMOTE	77.4	95.2	-	86.3	10-fold
[22]	SVM	96.34	97.46	96.34	97	
[24]	MLP	71			71	Hold out
[27]	SVM	95.71	87.87	94.36	93.20	
[28]	SVM	92.16	87.5	-	90.11	Hold out
[29]	SVM	-	-	-	89.2	Hold out
[30]	SVM	-	-	-	87.18	Hold out
[31]	Fuzzy Cognitive Map	-	-	-	86	Hold out
[32]	SVM	94.17	91.40	90	91.64	k-fold
[35]	Decision Tree	100	100	-	99.78	5-FOLD
[41]	ANN	99.26	99.42	99.31	99.3	Hold out

Figure 3.1 Accuracy Level

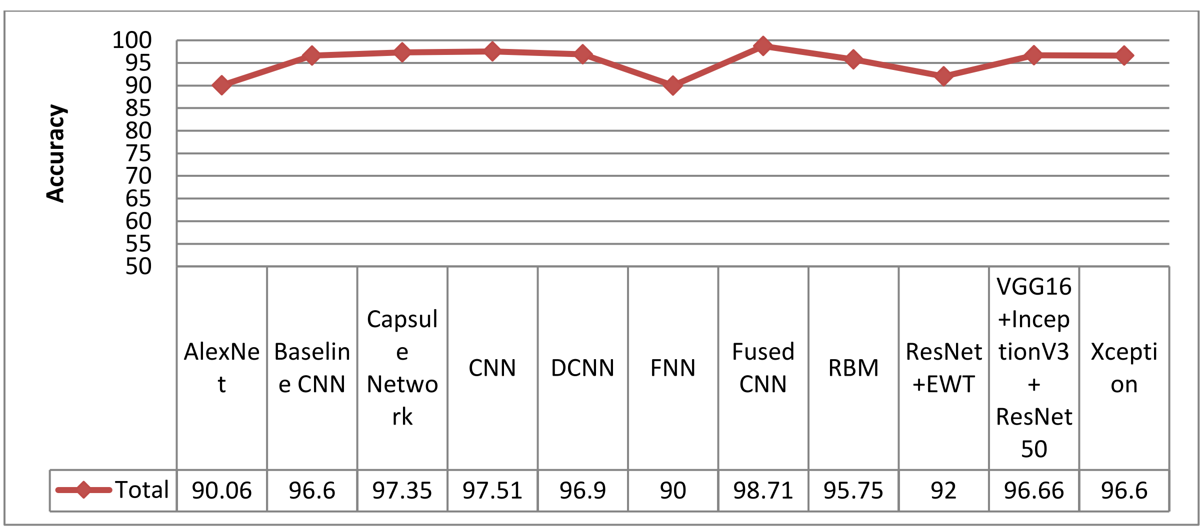


3.2 Summary of Deep Learning Models

Without the need for explicit feature engineering, deep learning models use the input data to learn hierarchical representations of features. The quality and accessibility of the data, the model's architecture, the adjustment of hyperparameters, and the use of suitable training and validation techniques all affect how well deep learning algorithms perform in the diagnosis of oral cancer. Furthermore, in order for deep learning models to function at their best, a lot of labeled data are frequently needed. DL algorithms do not need human feature extraction; instead, they may automatically learn features from unprocessed data. The following are a few popular deep learning algorithms for identifying oral cancer: Belief Network, CNN, Autoencoder, and Capsule Network. Promising outcomes in the identification and diagnosis of oral cancer have been observed in Table 3.2 and Figure 3.2.

Table 3.2 shows the performance metrics based on DL.

Ref	Classification Model	Sensitivity	Specificity	Precision	Accuracy	Validation
[11]	FCN	93	95	-	80.68	5-FOLD
[13]	DCNN	99.31	94.44	94.70	96.90	5-FOLD
[16]	Deep CNN	94	91	-	91.4	10-fold
[17]	RBM	93.26	94.74	-	95.75	Hold out
[20]	DCNN				90.08	-
[22]	CNN	97.67	97.34	97.35	97.51	k-fold
[23]	CNN	81	73.9	-	75.4	-
[27]	CNN	97.64	93.47	96.51	96.15	-
[33]	FNN	-	-	-	90	-
[34]	Capsule Network	97.78	96.92		97.35	10-fold
[36]	VGG16+InceptionV3+ ResNet50	98.33	95	95.16	96.66	Hold out
[37]	Xception	-	-	-	96.6	5-fold
[38]	AlexNet	87.38	90.15	-	90.06	
[39]	Fused CNN	-	-	-	98.71	10 fold
[39]	Fused CNN	-	-	-	98.71	10 fold
[40]	ResNet+EWT	100	89.29	-	92	
[43]	Baseline CNN	96	-	97	96.6	5-FOLD
[45]	CNN	86.6	90	-	88.3	Hold out



3.3 Summary of Transfer Learning

Using deep learning models that have already been trained on sizable datasets for a related task is known as transfer learning. The plan is to use the pre-trained model's learnt representations to improve it on a smaller, task-specific dataset. This makes it possible to transfer features and knowledge from the source work to the target task, particularly in cases where the destination dataset is small. Transfer learning-based identification techniques are displayed in Table 3.3 and Figure 3.3..

Table 3.3 shows the performance metrics based on Transfer Learning.

Ref	Feature Extraction Method	Classification Model	Sensitivity	Specificity	Precision	Accuracy	Validation
[21]	NasNet	DBM	93.75	-	96.15	95	Hold out
[26]	LeNet5	SVM	86	97.3	94.5	92.52	10-fold
[42]	Inception V3	XGBoost	98.99	-	96.3	96.3	10-FOLD
[44]	VGG19	Random Forest	99.3	100	-	99.65	33% data

3.4 Challenges and research gaps in oral cancer identification

These are some typical gaps in the body of knowledge about the use of artificial intelligence in oral cancer detection studies.

1. Limited dataset size: Many research suffer from small and unbalanced datasets, which can lead to overfitting and subpar model generalization. Larger and more diverse datasets are needed to improve prediction algorithms' accuracy and dependability. 7–9–12–14–22–36–37–38–44]

2. A lackluster investigation of features: Certain research might focus on a limited set of predictably identifiable traits. Examining novel imaging modalities like texture analysis or radiomics may produce more insightful information for the prompt detection of oral cancer. 10–11–13–14–18–22–30–31

3. Interpretability of Models: A lot of machine learning techniques, such deep learning models, used to predict oral cancer are commonly thought of as "black-box" techniques, which makes it challenging to assess the conclusions these models reach. Interpretable models or techniques are needed in order to comprehend the features underlying the forecasts. [14, 15, 18, 29, 31, 37]

4. Limited External Validation: Studies that only test their models on the training dataset risk producing performance forecasts that are unduly optimistic. External validation on a variety of datasets is necessary for evaluating the models' generalizability.[19,36, 7]]

5. Clinical usability: While most research focuses on improving prediction accuracy, it often overlooks how these models can be used clinically and how they can be integrated into the existing healthcare systems. It is critical to understand how the predictions may impact clinical judgment and patient outcomes for the implementation to be successful. [15, 21, 40, 41, 43]

6. Integration of Multi-modal Data: By combining them with information from other modalities, such histology, genetics, or clinical data, the prediction power may be increased. [23, 26, 39]

IV Conclusion

The incidence of oral cancer is growing. Pathologists may have difficulty identifying the lesions, despite the fact that histopathology is one of the best methods for detecting oral cancer. The methods and detection accuracy of the techniques outlined in this research may prove advantageous to the medical personnel. In this study, images are captured and several processes are performed to classify them as normal or aberrant. In conclusion, transfer learning uses pre-trained models to enhance performance by customizing their learned representations to the target task, whereas machine learning depends on human feature engineering. Deep learning, on the other hand, automatically learns features from unprocessed data. Particularly in situations with little labeled data, transfer learning, in particular, combines the advantages of pre-trained models with the flexibility to adapt to unique domains, making it a potent method for identifying oral cancer. Any machine learning algorithm's likelihood of success depends on the availability of data, the processing capacity of the machine, and further algorithm improvements. Some prospective areas for future study enhancement are listed below:

- Better and more precise results will emerge from future study on the traits that can be gleaned from data on oral cancer.
- Adding a hierarchical classifier to neural networks through optimization techniques.

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