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A systematic review of artificial intelligence techniques for oral cancer detection

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ABSTRACT

Oral cancer is a form of cancer that develops in the tissue of an oral cavity. Detection at an early stage is necessary to prevent the mortality rate in cancer patients. Artificial intelligence (AI) techniques play a significant role in assisting with diagnosing oral cancer. The AI techniques provide better detection accuracy and help automate oral cancer detection. The study shows that AI has a wide range of algorithms and provides outcomes in the most precise manner possible. We provide an overview of different input types and apply an appropriate algorithm to detect oral cancer. We aim to provide an overview of various AI techniques that can be used to automate oral cancer detection and to analyze these techniques to improve the efficiency and accuracy of oral cancer screening. We provide a summary of various methods available for oral cancer detection. We cover different input image formats, their processing, and the need for segmentation and feature extraction. We further include a list of other conventional strategies. We focus on various AI techniques for detecting oral cancer, including deep learning, machine learning, fuzzy computing, data mining, and genetic algorithms, and evaluates their benefits and drawbacks. The larger part of the articles focused on deep learning (37%) methods, followed by machine learning (32%), genetic algorithms (12%), data mining techniques (10%), and fuzzy computing (9%) for oral cancer detection.

1. Introduction

Oral cancer is a type of cancer that is defined as the uncontrollable proliferation of cells that invade and harm the surrounding tissue. Cell division that is out of control results in an unusual development in the mouth that resembles a tiny ulcer. Oral cancer is the type of cancer that ranks sixth in the world and is affecting globally. The risk of oral cancer is high in the men above 50 years than women [1,2]. The average age of occurrence of oral cancer is 63 years but it is also possible to occur in young people [2]. Oral cancer poses a serious health challenge to the nations undergoing economic transition [3]. In India, around 77,000 new cases and 52,000 deaths are reported annually and it is approximately one-third of global incidences [4] and it contributes 30% of different types of cancers [5]. The increasing number of cases in oral cancer poses a challenge in the community health and also affects the quality of health [6].

The main reason for the oral cancer is the lack of oral hygiene [7], excessive use of tobacco and alcohol [8,9]. Also in India, people chew betel leaf along with areca nut and may contain tobacco [10,11]. This is available in the market that may leads to addiction also. The sharp teeth and weak immune system also could be the reason for the occurrence of oral cancer. Another important reason for the occurrence of oral cancer is the change in the genetic organization [12]. There are 3 major types of oral cancer, namely Oral Squamous Cell Carcinoma (OSCC), verrucous carcinoma and minor salivary gland carcinomas. But the 90% of oral cancer occurs when squamous cells mutate and become abnormal [13]. The verrucous carcinoma contributes 3 to 5% of oral cancer and minor salivary gland carcinomas are even minimal [14].

The oral cancer spreads in different stages. The doctors usually identify in 2 stages as clinical and pathological [15]. But with the early detection of oral cancer, the survivability rate would be high. The reason for the early detection is to restrict the spreading of the cancer cells.

Oral cancer detection can be done using invasive and non-invasive methods. This survey focuses on non-invasive methods by either using images or datasets for the cancer detection. Image processing methods are used extensively to process the images collected from various sources. The input images are gathered from different scanning methods and are pre processed using the wide range of histogram equalization methods and employing various filters to remove the noise

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Table 1
Existing survey on oral cancer detection.

Ref.	Deep learning	Machine learning	Data mining	Fuzzy computing	Genetic algorithms	Techniques used in existing survey
[18]	✓	✓				Various Machine learning (ML) and Deep Learning (DL) techniques used for oral cancer and other cancer detection
[19]	✓					Mainly focuses on deep learning techniques used for various cancer detection
[20]	✓					Cancer detection based on histopathology images using different deep learning architectures
[21]	✓	✓				DL and ML techniques for histopathology based cancer detection
[22]		✓				Extensive survey on oral cancer detection using ML techniques
[23]	✓	✓				Automatic cancer detection for different types of cancers
[24]		✓	✓		✓	Mainly focused on various algorithms of machine learning
Our Survey	✔	✔	✔	✔	✔	**All the AI algorithms are explored in our survey**

and smoothens an image. Whereas invasive methods can also be used like the miniaturized devices to detect oral cancer [16].

An Artificial Intelligence (AI) techniques are used in different domains to improve the performance because of its ability to learn and predict. It is used in the detection of oral cancer and it performs exceptionally good. Artificial intelligence techniques provides a good platform by employing wide range of algorithms which performs better and provides precise results [17].

1.1. Motivation

Oral cancer is a form of cancer which is usually recognized at advanced stage either because of ignorance or due to lack of medical facilities. This is more prominent in the mid or low income countries where people are deprived from medical facilities [25]. In such cases, the mortality and morbidity rate will be high. To avoid that, an early detection of oral cancer plays a very important role.

The rich source of AI techniques and tools provides a cost effective methods in the detection of oral cancer. This will benefit doctors as an expert tool and also helpful in further investigations. The evolving computer algorithms are providing finest solutions in diagnosing other types of cancers and diseases. Table 1 shows the existing survey on the oral cancer detection using various AI techniques. It shows that the focus is more on machine learning and deep learning and it also covers the different types of cancers. Our survey focuses specific to oral cancer detection and also includes some of the other techniques including machine learning and deep learning.

1.2. Contribution

The study covers 73 papers that presents the various methods and techniques for the early detection of oral cancer. It provides a comprehensive idea about the overall process involved in the detection of oral cancer. The major contributions of this study are:

1. Summarize and synthesize various artificial intelligence techniques used for oral cancer detection.
2. Show the advantages and disadvantages of each technique used in oral cancer detection.
3. Presents important evaluation metric accuracy in the detection of oral cancer.
4. Provide the knowledge of factors used for oral cancer detection.
5. Demonstrate the opportunities and challenges of automating oral cancer diagnosis.

The organization of the survey begins with introduction and Section 2 provides the methodology used in the survey. Image processing techniques and steps are discussed in Section 3. The comprehensive overview of AI techniques used in the detection of oral cancer is given in Section 4. Finally the study is concluded with the remarks.

Table 2
Literature sources.

Database	Primary relevant	Articles retained
IEEE Explore	46	29
Elsevier	21	10
Springer	15	4
John Wiley	4	1
Inderscience	5	2
Hindwai	5	2
Taylor & Francis	2	1
Others	13	24
Total	**109**	**73**

2. Survey methodology

The survey follows the holistic research methodology to provide an overview of different methods in detecting the oral cancer.

2.1. Systematic review and mapping

The following Research Questions (RQ) are considered to carry out the survey.

RQ1. Which type of input provides the most accurate results?

RQ2. What are the different AI techniques used in the detection of oral cancer?

RQ3. Which type of AI technique is most widely used?

RQ4. Which AI technique provides the best detection accuracy?

RQ5. Which software tools are used in implementation?

RQ6. What are the issues and challenges faced in the oral cancer detection?

Inclusion Criteria:

1. Research article should focus on detection of an oral cancer using AI technique.
2. Research article should take input either from an images or dataset.
3. Research article should focus on obtaining high accuracy of greater than 80% in detecting an oral cancer.

Exclusion Criteria:

1. Research article not presented in engineering or technology domain.
2. Research article published in workshops and book chapters.
3. Research article focused on biomarkers as the means of detection of oral cancer.

Table 3
Publication source of research articles considered for survey.

Publication source	No.
Transactions	
IEEE Transactions on Biomedical Engineering	1
IEEE Transactions on Biomedical circuits and systems	1
Journals	
EAI Endorsed Transactions on Energy Web	1
IEEE Systems Journal	1
IEEE Journal of Biomedical and Health Informatics	2
Neural Networks	1
Journal of King Saud University-Computer and Information Sciences	1
Journal of Clinical Medicine	1
Tissue and Cell	1
Journal of Medical Engineering	1
Cancer Reports	1
Measurement	1
Biomedical Optics Express	2
Int. J. Adv. Netw. Appl.	2
International Journal of Applied Engineering Research	1
International Society for Optics and Photonics	4
Biomedical Signal Processing and Control	3
Sensors	1
IEEE Access	2
IETE Journal of Research	1
Scientific Reports	1
Medico Legal Update	1
Journal of Cancer Research and Clinical Oncology	1
Journal of Medical Systems	2
Journal of Multimedia Information System	1
Oral surgery, Oral Medicine, Oral Pathology and Oral Radiology	1
Heliyon	1
PloS one	1
International Journal of Medical Engineering and Informatics	1
International Journal of Advanced Intelligence Paradigms	1
The Scientific World Journal	1
Int. J. Data Min. Tech. Appl	1
International Journal of Recent Technology and Engineering	2
PeerJ	1
Turkish Journal of Physiotherapy and Rehabilitation	1
International Journal of Pure and Applied Mathematics	1
Journal of Taibah University Medical Sciences	1
Procedia Computer Science	1
Conference	
38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)	3
IEEE 33rd International Symposium on Computer-Based Medical Systems (CBMS)	1
2019 IEEE International Conferences on Ubiquitous Computing \& Communications (IUCC) and Data Science and Computational Intelligence (DSCI) and Smart Computing, Networking and Services (SmartCNS)	1
The 16th International Conference on Biomedical Engineering	1
IEEE 17th International Symposium on Biomedical Imaging (ISBI)	1
IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018	1
2018 IEEE 8th Annual Computing and Communication Workshop and Conference (CCWC)	1
2017 International Conference on Inventive Communication and Computational Technologies (ICICCT)	1
2016 International Conference on Systems in Medicine and Biology (ICSMB)	1
Third World Conference on Complex Systems (WCCS)	1
2014 IEEE International Symposium on Signal Processing and Information Technology (ISSPIT)	1
International Conference on Communication and Electronics Systems (ICCES)	3
IEEE International Conference on Bioinformatics and Biomedicine (BIBM)	3
IEEE International Conference on Healthcare Informatics (ICHI)	1
International Conference on Micro-Electronics and Telecommunication Engineering (ICMETE)	1
International Conference on Computational Performance Evaluation (ComPE)	1
National Conference on Science, Engineering and Technology (NCSET–2016)	1
2023 7th International Conference on Intelligent Computing and Control Systems (ICICCS)	1
Total	73

Table 4
Most cited papers in the literature.

References	[26]	[27]	[28]	[29]	[30]	[31]	[32]	[33]	[34]	[35]
No. of Citations	203	197	164	94	97	89	82	77	74	65
References	[36]	[37]	[38]	[39]	[40]	[41]	[42]	[43]	[44]	[45]
No. of Citations	57	53	52	29	29	28	28	27	26	26

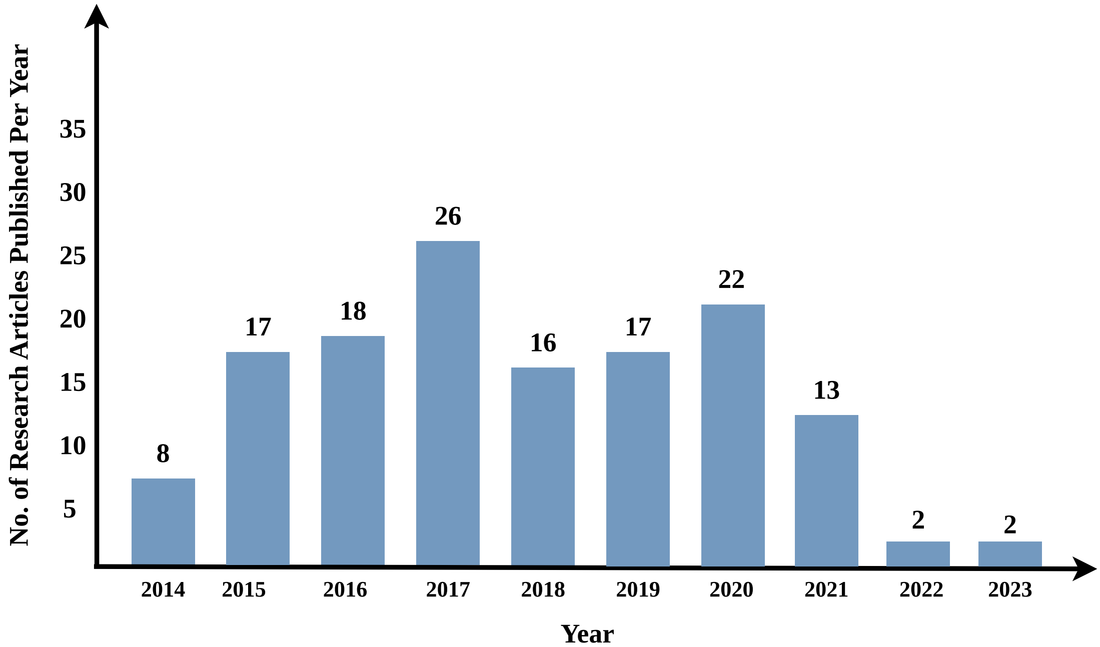

Fig. 1. Articles Published to detect Oral Cancer Using AI Techniques.

2.2. Literature sources and search strategies

The research articles are collected from 2014 to 2023 from various international journals and conferences. The research articles are acquired from IEEE xplore, Elsevier, Springer, Inderscience etc. The research articles published in conference proceedings also considered in our survey. Table 2 shows the literature sources used in the collection of research articles. 109 articles are collected from different sources. Upon going through the RQ, inclusion and exclusion criteria, 73 papers are retained for the survey. Table 3 shows the publication source of each research article used in the survey. Table 4 shows the 20 most cited articles used in the study.

Fig. 1 shows the statistics of the research articles published in different journals from year 2014 to 2023 to detect oral cancer that we considered in our survey. It is observed from the graph that the research has picked up in the year 2017 and continuing with more advancements happening in the field.

3. Image processing

Digital Image Processing (DIP) is the process of applying an algorithm on digital images in the computer system. It is a sub field of signals and systems focused on images. DIP is a technique to perform an operations on a digital image to get an enhanced image or extract some useful information. Image processing is used in various applications such as processing color, video and so on. One of its important applications is in medical field.

Image processing performs the image enhancement and restoration which is helpful in processing the image by removing noise and distortion. A huge set of methods are available to perform this task.

The first step is to collect an image from various sources such as

- Microscopic image (Biopsy sample observed in microscope and connected to a computer to get a digital image)
- X-ray image
- MRI image
- CT Scan image
- PET Scan image
- Color image (captured from mobile phone)

Fig. 2 shows the graph of the different types of input research articles used in the survey. Majority of the research articles used histopathology image, that is an image taken from the microscope. The reason for choosing histopathology image is to get the most accurate results. A fair share of images from different types of scanning are also used. A good repository of histopathology images are available for computation [46].

Apart from images the study also focuses on another type of input that is extensively used is the data set that is created from the selected attributes from patient data and the genetic data contains an information about genes, chromosomes and other relevant attributes to form the data set which will be applied to genetic algorithms. Fig. 3 shows the steps followed in detecting the oral cancer when the digital images are provided as an input. The following section explain these steps in detail.

3.1. Image enhancement

The objective of an image enhancement is to improve the quality of an image by improving the brightness and contrast, adjusting the angles and removing the noise using various filters. There are several methods and techniques available to preprocess the images collected from different sources. It uses several filters and transformation to process the image. Some of the important image enhancing methods used in our study are

- Histogram Equalization methods
- Adaptive local Histogram equalization technique [47]
- Control Enhancement Adaptive local Histogram equalization (CLAHE) [48]

and filters such as

- Savitzky–Golay filter [37]
- Median filter [22]
- Gabor filter [49,50]
- Adaptive median filter [51]
- Anistropic diffusion filter [52]

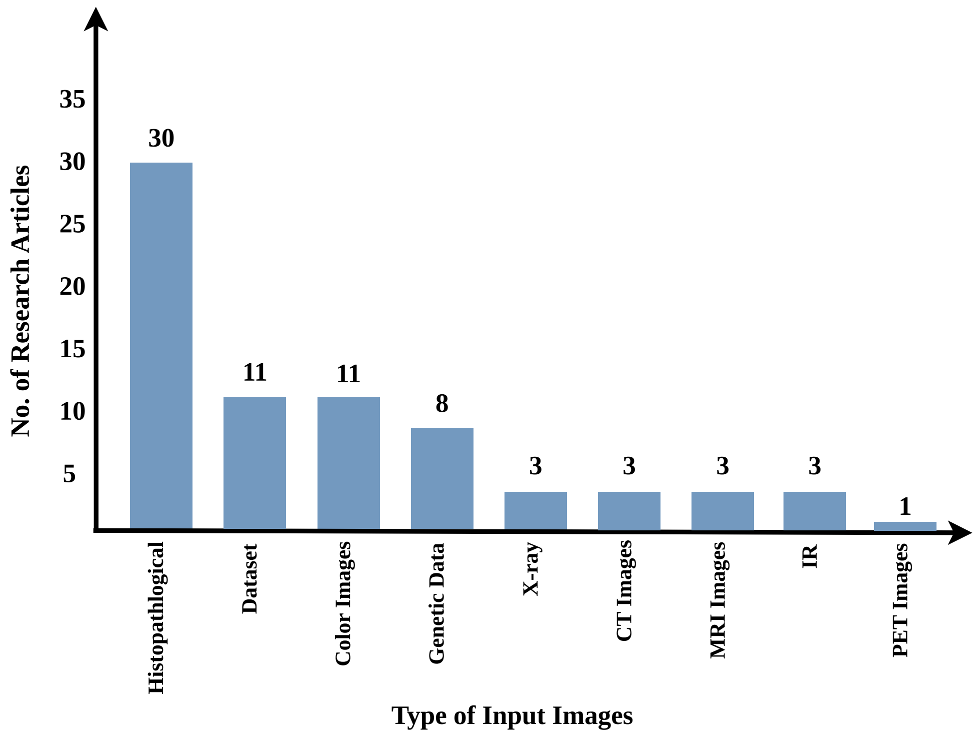

Fig. 2. Types of Input used in survey.

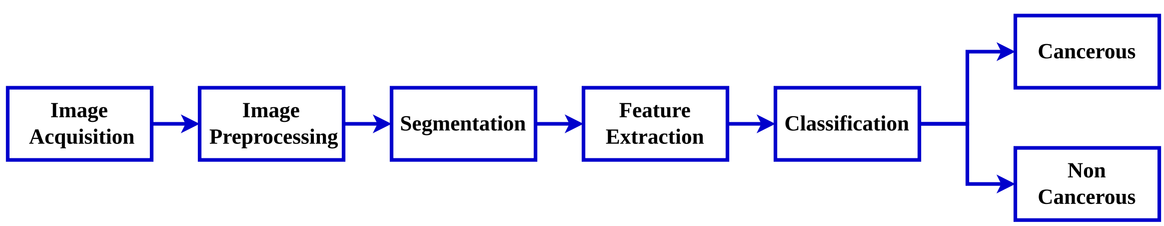

Fig. 3. Steps in the Detection of Oral Cancer.

3.2. Image segmentation

Segmentation is the process of dividing an image into multiple sections called segments. These segments are helpful to analyze the digital image in a simple way. This helps in medical field with the ability to provide faster and efficient diagnosis.

The Table 5 lists some of the segmentation techniques used in our survey along with its advantages and disadvantages [53–57].

The important techniques in segmentation contains both traditional approaches as well as AI techniques. The basic and popular segmentation methods are threshold methods [62] such as 2D (2 Dimensional) entropy threshold, Ostu's threshold and k-means clustering [63,64].

3.3. Feature extraction

Feature extraction is concerned with deriving a specific data from segmented image. This specific information greatly helps in reducing the storage space and the computational complexity. This specification is important as it may affect the performance of the classification algorithm because of over fitting issue [68]. The features can be texture, shape, color etc [69]. Some of the feature extraction techniques used in this survey are Gray level cooccurence matrix (GLCM), feature transfer learning [70], Hu's moment extraction [58] and so on. Deep learning is a very efficient in automating the feature extraction process [71].

3.4. Classification

Classification refers to the division of data in to specific classes. Oral cancer detection uses classification to detect whether the given data is cancerous or non-cancerous. This is referred as a binary classification. Multi-class classification can also be performed to identify the different stages of cancer [72]. There are a wide range of classifiers used in this survey and the accuracy is also documented [73].

Table 6 shows the summary of various image processing, segmentation and feature extraction techniques used in our study to detect oral cancer.

These steps can also be performed in parallel to improve the operational speed of the algorithms using tools like NVIDIA graphical processing unit [74].

4. Artificial intelligence techniques

There are several AI techniques that can be used in the segmentation, feature extraction and classification process in order to obtain tremendous performance in the early detection of oral cancer [64] . In this survey, we are outlining most of the AI techniques that are used in the detection of oral cancer.

Fig. 4 shows the different AI techniques focused in our study for the oral cancer detection.

The AI techniques immensely helps in automating the detection and classification of oral lesions or tumors. The following are the techniques that we analyzed in our survey for oral cancer detection.

Table 5
Types of segmentation techniques.

Publication	Year	Approach	Description	Methods	Advantages	Disadvantages
Dev Kumar Das et al. [58]	2014	Threshold method	Comparing the pixel intensity of an image with the threshold value	Simple thresholding, Ostu's Binarization, Adaptive Thresholding	Simple process	Prone to errors
Arumugum et al. [59]	2019	Region based method	Creating segments based on common characteristics	Region growing, Region splitting and merging	Good for noisy images	Consumes more resources
Rahman et al. [40]	2019	Edge based method	Locating edges as it consists of compelling information	Gradient based methods, Gray Histograms	works well for images with good contrast among objects	Not good for noisy images
M Sujatha et al. [60]	2021	Clustering based segmentation methods	Getting an object by cutting into k clusters	k-means clustering, Fuzzy C means	Efficient for real time application	Identifying cost function is difficult
Rajdeep Mitra et al. [61]	2016	Watershed method	Uses topographical information to get objects	NA	Provides the stable segments	Gradient computation for ridges is difficult
Wan-Ting Tseng et al. [31]	2015	Artificial neural Networks	Based on Deep learning algorithms	Convolutional Neural Networks (CNN)	Implementation is easy	Consumes more time

Table 6
Image processing techniques.

Publication	Year	Preprocessing technique	Segmentation method	Feature extraction
Rahman et al. [40]	2019	Median filter	Prewitt method	Gray level length matrix
Dev Kumar Dasl et al. [58]	2014	Morphological Filtering	Ostu's thresholding	Hu's moment extraction
Ahmed et al. [65]	2017	High pass filter	Gray level thresholding	Firefly algorithm
Paritosh Pande et al. [66]	2016	Optical coherence tomography angiography (OCT) scan	K means clustering	Gray level run length method (GLRL)
Rajdeep Mitra et al. [61]	2016	Linear contrast stretching	Watershed segmentation	GLCM
Shilpa Harnale et al. [52]	2019	Anistropic diffusion filter	k-means and Fuzzy C-Means (FCM)	GLCM
Yusra Y. Amera et al. [38]	2015	Contrast enhancement	Ostu's thresholding	Connected component labeling
M. Chakraborty et al. [48]	2017	CLAHE	Interactive graph cut algorithm	Thermal discreening patterns
Albasri et al. [67]	2015	Normalization	Expectation maximization (EM) algorithm	Principal Component Analysis (PCA) and local adaptive thresholding

- Machine Learning
- Deep Learning
- Fuzzy Computing
- Data mining techniques
- Genetic algorithms

The confusion matrix is used to calculate the performance of classification. True Positive (TP), False Positive (FP), True Negative (TN), False Negative (FN) are obtained from the confusion matrix. The performance metrics such as accuracy (A) sensitivity (SN), specificity (SP), F measure, Area Under Curve- Receiver operating Characteristics (AUC-ROC), Matthews's Correlation Coefficient (MCC) are calculated using Eqs. (1)–(8) are outlined in our study. Accuracy specifies the amount of samples that are correctly classified. The percentage of positive samples that are accurately categorized is known as sensitivity. The percentage of negative samples that are correctly categorized is known as specificity. BCR is defined as the geometric mean of sensitivity and specificity. The harmonic mean of precision and recall is known as the F measure. The importance of binary class classifications is gauged using MCC. AUC-ROC shows the efficiency of binary classifier model performs at different threshold settings. Intersection over Union (IoU) is for assessing object detection performance by contrasting the predicted bounding box with the ground truth bounding box. Mean Squared Error (MSE), Mean Absolute Error(MAE) and Root Mean Square Error (RMSE) also documented in some of the articles. Positive Predictive Value (PPV) and Negative Predictive Value (NPV) is mentioned in some

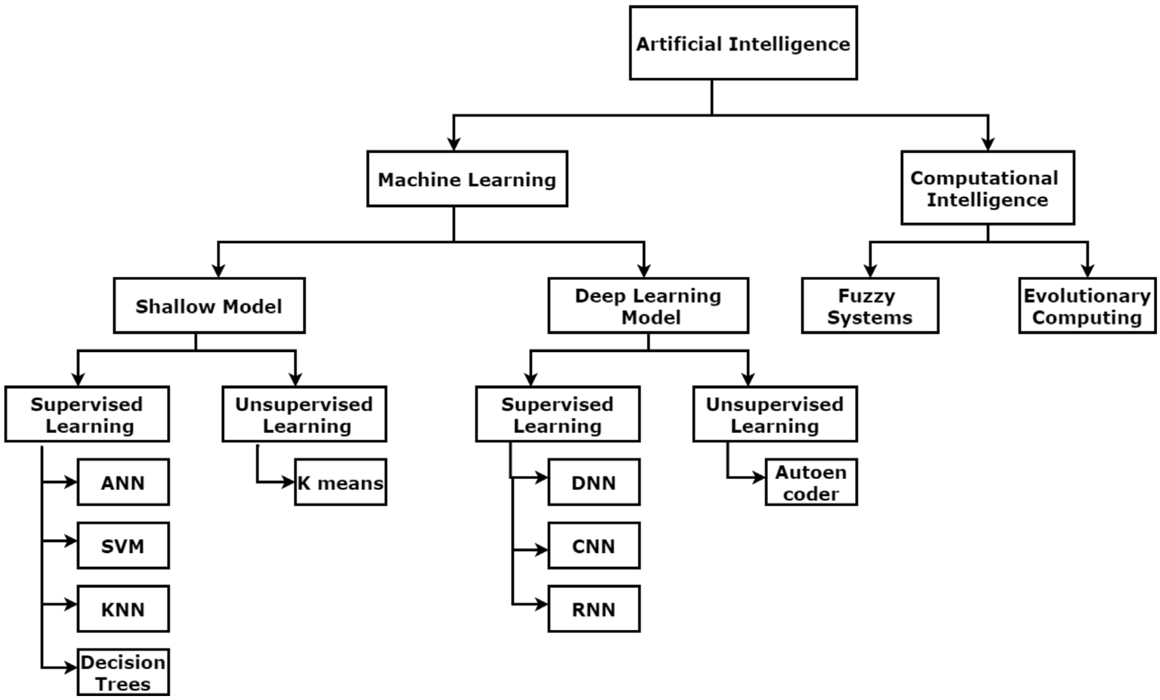

Fig. 4. AI Techniques Focused in the Survey.

of the research articles that are useful in interpreting the results.

$$Accuracy(A) = \frac{Correct\ Predictions}{Total\ Predictions} \tag{1}$$

$$Sensitivity(SN) = \frac{TP}{TP + FN} \tag{2}$$

$$Specificity(SP) = \frac{TN}{TN + FP} \tag{3}$$

$$BCR = \sqrt{(SN * SP)} \tag{4}$$

$$Precision(PR) = \frac{TP}{TP + FP} \tag{5}$$

$$Recall(R) = \frac{TP}{TP + FN} \tag{6}$$

$$F\ measure = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{7}$$

$$MCC = \frac{TP * TN - FP * FN}{\sqrt{(TP + FN)(TP + FP)(TN + FN)(TN + FP)}} \tag{8}$$

4.1. Machine learning

Machine learning is section of artificial intelligence that has a broad set of algorithms and has the capability to learn from the data to make decision and prediction [75,76]. Machine learning is effective in identifying different types of cancer [77]. These algorithms works efficiently on labeled and unlabeled data. The algorithm would be trained iteratively to create the model. Then a model would be tested for the new data and can observe the improvement in accuracy. The inconsistent data can be tuned using belief merging [78]. Significant work is going on in the detection of various kinds of cancer using machine learning techniques. The same is extended for the detection of oral cancer.

In this section we have referred 19 research articles listed in Table 7, that uses different machine learning algorithms for the oral cancer detection and analysis.

Rahman et al. [79] compared five different machine learning classifiers out of which decision tree provides the highest classification accuracy and the sensitivity, specificity and precision is also high at 100%. As per the study suggested by Mukta Sharma et al. [80], AdaBoost classifier provides highest accuracy. Rajaguru et al. [81] uses the Multi layer Perceptron (MLP) classifier, Extreme Learning Machines (ELM) classifier and Gaussian Mixture Model (GMM) classifier along with various activation function to identify the four different stages of oral cancer. Marsden et al. [44] suggested different classifiers in their study and the Random forest method is found to be providing the absolute results. Ming-Jer Jeng et al. [37] not only discussed about the analysis of cancer regions using various methods in his study but also tried to analyze the survivability rate. Rahman et al. [40] again came up with the comparison of three different classifiers achieving an ideal accuracy. Rajesh Kumar et al. [26] showed in their study that k-nearest neighbor algorithm also can be decisive in finding the oral cancer.

Support vector machine (SVM) is one of the highly sought supervised machine learning algorithm that we have come across in this study for identifying the oral cancer. Zhalong Hu et al. [83] used SVM along with image pre processing technique and Fuzzy C-means segmentation method. D.Padmini Pragna et al. [51] developed a tool to identify oral cancer using SVM and other classifier, where K nearest neighbor (KNN) classifier provides the top-notch accuracy. Banerjee et al. [84] also uses SVM to identify the cancerous element using textural features. SVM algorithm is also adapted by Bourass Youssef et al. [85] by providing a tool that helps doctors in making decisions and also uses hierarchical model for selecting the features.

Dev Kumar Das et al. [58] demonstrated the Classification and Regression Tree (CART) model that can be used to automate the segmentation of the mitotic cells in analyzing OSCC. Paritosh Pandey et al. identifies the pre-cancerous region that is very helpful in increasing survivability rate. Harikumar Rajaguru et al. [86] discussed on the over consumption of alcohol and tobacco can lead to the development of OSCC. They also classified into different stages of oral cancer. The comparison of Softmax Discriminant Classifier with other classifiers is done to validate the model and Softmax Discriminant Classifier proved to be good in identifying the different stages of cancer. Shilpa Harnale et al. [52] provides a non-invasive, cost efficient way

Table 7
Summary of machine learning techniques in the oral cancer detection.

Publication	Year	Problem addressed	Modality and size of data set	Data set source	Algorithm	Performance metrics	Advantages	Disadvantages
Rahman et al. [79]	2020	Study of morphological and textural features	Biopsy-452 images	diagnostic center	SVM, logistic regression, linear discriminant, kNN and decision tree classifier	A : 99.78 SN : 100 SP : 100	Capability to predict outcomes from novel, unforeseen inputs	Training time is high
Mukta Sharma et al. [80]	2019	Meta-learning Techniques for optical diagnosis	Raman Spectroscopic –110 images	Chang Gung Medical Foundation, taiwan	Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA) and AdaBoost classifiers.	A : 93–95	It is rapid, realistic, label-free and inexpensive.	Prone to Overfitting
Rajaguru et al. [81]	2017	Analysis of TNM (Tumor, Node, Metasis) using classifiers	Patient data-75 patients	Department of Oncology of G Kuppu swamy Naidu Hospital (GKNM) Hospital	MLP and GMM classifiers, ELM	A : 94.1 SN : 87.4 SP : 89.94	Performs classification at different stages of oral cancer	–
Hameed et al. [82]	2020	Automatic image analysis technique	Micro scopic image-53	Department of Oro-maxillo facial Surgical & Medical Sciences, Faculty of Dentistry	SVM	A: 98.01 SN : 98.86 SP : 94.74	Feature can be simply extracted from the blue component	Difficulty with Noisy Data or Overlapping Classes
Marsden et al. [44]	2020	To check diagnostic ability as intraoperative guidance	Histo logical-53	University of California Davis Medical Center	1D CNN, SVM, Random forest	A : 90 AUC-ROC : 0.88	Contrast agents are not needed	Generation of accurate tissue condition
Ming-Jer Jeng et al. [37]	2019	Detection using sub-site-wise differentiation	Micro scopic-80	Chang Gung Memorial Hospital, taiwan	LDA and QDA	A : 81.25 SN: 90.90 SP: 83.33	Fast, Cost effective, no need of labeling	–
Rahman et al. [40]	2019	Extraction of color, shape and texture for detection	Micro scopic image-42	Ayursundra Healthcare Pvt. Ltd, Guwahati	1. Decision tree (DT) 2. SVM 3. Logistic regression	1. DT- 99.4% 2.SVM-100% 3. Logistic regression-100%	Accurate and computationally efficient	Real time deployment need to be validated
Rajesh Kumar et al. [26]	2015	Detection using biologically interpretable features	Micro scopic-2828	Hospitals	k-nearest neighbor	A : 92 SN : 91.64 SP : 80.17 F measure : 79.53 MCC : 71.64	High performance	Evaluated only for 4 tissues
Zhalong Hu et al. [83]	2018	Early detection of minute tumors in edge area of image	CT images-91	Hospitals	SVM	A : 90.11 SN : 87.5 SP : 92.15	Minute tumors also can be detected	Need an expert to label the dataset
Pragna et al. [51]	2017	Develop an health alert system	CT images-29	oncologist	SVM	A : 97 PR : 97.5 R : 97.5 F measure : 96.2	Robust to Overfitting	–
Banerjee et al. [84]	2016	Detection using textural features	Micro scopic image-23	Gurunanak Institute of Dental Science and Research	SVM	A :100 SN : 81.3 SP : 91.3	Non invasive diagnostic tool	–
Youssef et al. [85]	2015	Provides platform to help surgeons in decision making	color images-4160 images	Dental Surgeons of Hospital Ibn Rochd	SVM	A : 82 PR : 80 R : 70	It converges to a global optimal solution	Patch extraction is poor
Dev Kumar Dasl et al. [58]	2014	To develop a computer assisted segmentation of mitotic cell	histological slides-75	Dept. of Pathology, Midnapur Medical College and Hospital, India.	CART algorithm	A : 83.80 PR : 83.8 R : 73.5 F measure : 78.3	Excellent cells for filtering mitotic cells	Considered only for one type of cell
Pande et al. [66]	2019	Detection using Optical method	Histopa thological image-153	morphological and biochemical information is used	Random forest algorithm	A : 87.40 SN : 88.2 SP : 92.2	Resilience to noise	Complex nature of histopathological data
Rajaguru et al. [86]	2017	Oral cancer classification using SDC	Data from various reports-75 patients	Hospitals	Softmax Discriminant Classifier (SDC)	A: 97.29 SN :89.74 SP : 100	Improved accuracy	Sensitivity to outliers
Shilpa Harnale et al. [52]	2019	Showcased hybrid method for segmentation in detection	MRI image-40 cases	Hospitals	SVM	A : 98.04	Efficient algorithm to detect lesions	Sensitivity to parameter tuning
Rajaguru et al. [87]	2017	Classification of risk level using hybrid method	data set-75 patients	Oncology department of G Kuppuswamy Naidu Hospital (GKNM), Coimbatore	Hybrid ABC-PSO Classifier, BLDA Classifier	A : Hybrid ABC-PSO Classifier-100%, BLDA Classifier-83.16%	Misclassification of data is effectively managed	–

(*continued on next page*)

Table 7 (*continued*).

Publication	Year	Problem addressed	Modality and size of data set	Data set source	Algorithm	Performance metrics	Advantages	Disadvantages
Shams et al. [45]	2017	predicting the oral cancer development using genetic data	Genetic data-86 patients	www.ncbi.nlm.nih.gov/geo.	SVM, Regularized Least Squares (RLS), MLP with back propagation and deep neural network (DNN)	A : DNN-96%, SVM and MLP-94%	Effectively identifies the genetic differences	Non linearity in the data
Chakraborty et al. [48]	2017	non-invasive computer-aided method for detection	IR images-203	Hospitals	SVM	A : 84.72	Effective with small datasets	Piling up more scales degrades the performance
Manikandan et al. [88]	2023	Improved oral cancer detection using SVM	Patient data	Public dataset	SVM	A : 94.78	Hybrid feature selection techniques	–

to detect the cancerous region. It achieves the excellent accuracy in classifying the oral lesions as cancerous and non cancerous. Rajaguru et al. [87] also discussed about classifying the oral cancer with different stages that almost matches the results obtained from procedures followed in hospitals. They used Hybrid Artificial Bee Colony optimization algorithm- Particle swarm optimization (ABC-PSO) Classifier, Bayesian Linear Discriminant Analysis (BLDA) Classifier and achieved an excellent results.

Wafaa K. Shams et al. [45] demonstrated on predicting the oral cancer using genetic data. After extracting features using Fisher discriminant analysis from gene expression, it is given to 4 different classifiers, in which Deep Neural Network classifier performs better with high classification accuracy. Chakraborty et al. [48] uses the textural features and the kernel SVM in order to identify whether the acquired Infrared image is benign, malignant or pre-cancerous. The use of Gabor filters are performing well in extracting the features so that SVM performs the classification effectively. Nawandhar et al. [89] proposed a classifier that has to be mainly used for biopsy images to identify OSCC in epithelial cells. They used a various type of features like textural, gradient and shape. The detection accuracy observed is 95.56%. Manikandan et al. [88] demonstrates the use of the unified medical system with hybrid features selection approaches to determine the characteristics that are most helpful for the identification of oral cancer indirectly reduces the diversity of features that are gathered from various patient records in this study.

This section shows a wide range of classifiers that are used to train and test the data to detect an oral cancer. It is observed in our survey that these classifiers are extremely helpful in classifying the images thus by providing the high detection accuracy. The most used classifier is the support vector machine that provides accurate results.

4.2. Deep learning

Deep Learning is a core of AI technique and a subset of machine learning based on the multi layer artificial neural network that is capable of simulating the human brain. The important property of deep learning is that it requires a large amount of data, that increases the processing power but greatly reduces the time in testing and provides an end-to-end solution. Deep learning is very efficient in automating the segmentation, feature extraction and classification process in detecting an oral cancer [90].

Table 8 lists summary of the deep learning techniques used in our study to detect oral cancer. The architectures used predominantly here is Convolutional Neural Networks (CNN) [91–93] and Deep neural networks (DNN). Convolutional neural networks are mainly are used to analyze images. CNN is an artificial neural network that has the capability to identify patterns. It has a hidden layers called convolutional layer that are responsible to automatically recognize and extract spatial feature from input data. It contains the number of filters that has a ability to identify different components in the images. Another important component of the CNN is the pooling layer that has responsibility for reducing the size, parameters and computation in the network. The fully connected layers are the last layers in the network that receives the input from last convolutional or pooling layer. CNN are also used without the fully connected layer and is referred as Fully convolutional Network (FCN) [90]. CNN can perform both supervised and unsupervised learning.

S. Shetty et al. [94] proposed a hybrid optimization model combining Aquila Optimizer(AO) and Wildebeest Herd Optimization (WHO). The ensemble model is used for the oral cancer detection using optimized CNN to adjust the weights and SVM and MLP for classification of disease. They employed the improved version of linear discriminant analysis in order to reduce overfitting and training time and to improve the accuracy. The proposed model produced a error free results. This is proposed to deploy in cloud environment for easy access. Rahman et al. [95] proposed a Alexnet based transfer learning model for the oral cancer detection. This is a simple, affordable model for the early detection of oral cancer. Welikala et al. [32] demonstrates the bounding box annotations that is helpful in object detection. The input is an image taken from mobile phone, that is a cost effective and easy way for the people to reach clinicians. The use of laser endoscopic images provides a great detection accuracy and is also recommended because of ease and reach. Shipu Xu et al. [41] developed a 3 Dimensional Convolutional Neural Network (3D CNN) using 3D convolution kernel, that demonstrates the feature extractor generating multi channel information. It is nothing but a three dimensional feature that compute feature representation and produces output in 3D convolutional space. The comparison for 2D and 3D CNN are done for early detection of oral lesions and 3D CNN produces 6% higher accuracy than 2D CNN. P. R. JEYARAJ et al. [96] provided a mechanism to extract the higher level features from trained deep Boltzmann machine. They designed, developed and validated SVM, SVM-PCA, Deep Boltzmann machine (DBM) model to create the fusion classifier and is implemented using majority voting method. This removes the irrelevant feature and needs only lees amount of data to train.

The efficient use of Deep Convolutional Neural Networks (DCNN) along with the texture map for oral cancer detection is well demonstrated by Chih-Hung Chan et al. [42]. The two dimensional gabor filter and discrete wavelet transformation are used to obtain the texture image. This is fed as an input to the DCNN to obtain Region of Interest (ROI) marking. The classification model is implemented using deep convolution architectures like Residual network architecture and Inception model architecture and the semantic segmentation is implemented using Fully Convolutional Network (FCN) and Feature Pyramid Network (FPN). Texture centric CNN is also discussed by Wetzer et al. [97]. Binary CNN is used in cancer screening using texture data. Matias et al. [98] used Faster Region based Convolutional Neural Network (R-CNN) that takes care of the process of segmentation, cell nuclei detection and classification of cell that is completely based on the structure and function of the cell. Resnet 34 and Resnet 54 is used in this process. Navarun Das et al. [36] automated the process for multi class classification using CNN with transfer learning. The training models used are VGG-19, VGG-16 and Resnet 50. Histopathological findings are crucial to understand more about cancer cells and these

Table 8
Summary of deep learning techniques in the oral cancer detection.

Publication	Year	Problem addressed	Modality and size of data set	Data set source	Algorithm	Performance Metrics	Advantages	Disadvantages
S. Shetty et al. [94]	2022	Distributed framework using cloud	Histopathological image dataset −1224	github.com	AO+WHO optimization model	A : 92.17	Used improved version of LDA	–
Rahaman et al. [95]	2022	Transfer learning to improve detection	Histopathological image dataset	Public repository	Alexnet based transfer learning model	A : 97.66 SN : 92.74 SP : 87.38 F measure : 90.15	Customized layer methods improves accuracy	AlexNet is considerably large and increases complexity
Welikala et al. [32]	2020	Automating the identification of malignant lesions	Mobile phone image −2155 Image	MemoSa project	Faster R-CNN	A : 84.77 PR : 46.61 R : 37.16 F measure : 41.35	Bounding box annotations from multiple clinicians	Multiclass classification is poor
SHIPU XU et al. [41]	2019	3DCNNs-based image processing algorithm	3D CT image-7,000	oral Oncologist	3D CNN	A : 79 AUC : 79.6 SN : 81.8 SP : 73.9	High classification accuracy	Data expansion is needed
Jeyaraj et al. [96]	2020	Proposed classifier fusion	Hyper spectral-25 images	Emory University School of Medicine	Fusion algorithm	A : 94.75 SN : 90 SP : 87.5	Increases sensitivity of mixed pixel detection	need to validate for large dataset
Chih-Hung Chan et al. [42]	2019	Automated detection using DCNN combined with texture map	Redox ratio Images-80		FCN anf FPN	A : 92.34 SN : 93.14 SP : 94.75	Segmentation is greatly improved	test set is randomly selected
Wetzer et al. [97]	2020	Efficient automated processing of cancer screening data	Gray-scale-80 images	Dept. of Orofacial Medicine, Folktandvrden Stockholm	Binary CNN	A : 81 F measure : 84.85	Excellent performance in texture classification	Not as efficient as the Local Binary pattern (LBP)-based approaches
Matias et al. [98]	2020	To make a pipeline for nuclei classification and localization	Microscopic-22,200 images	University of Santa Catarina	Faster R-CNN	A : 88 F measure : 0.86 IoU : 0.76	Provides an alternate method for detection	Data set can be enhanced
Navarun Das et al. [36]	2020	Multiclass classification	Histopathological-156 images		CNN	A : 97.5 PR : 80.5 R : 78.3	Improved Accuracy	More images needed to improve the architecture
Panigrahi et al. [99]	2020	Automated computer aided method	Histopathological-150 images	GDC portal	Capsule Network	A : 97.35 SN : 97.78 SP : 96.62 PR : 96.9 F measure : 97.33	High throughput	Need to validate for large dataset
Folmsbee et al. [100]	2018	Method to train CNN using Active learning	Microscopic-143 images	Erie County Medical Center.	Active Learning	A : 96.44	Higher performance than Random learning	Class imbalance
Anantharaman et al. [33]	2018	Algorithm for object detection and segmentation	Color image-40	Google images	Mask R-CNN	A : 74.40	Cold sores and cankers sores segmentation done successfully	–
Anantharaman et al. [101]	2017	To develop an tool for field workers	Color image-6	Hospitals	Random Forest Classifier algorithm	A : 66	Decision support tool	–
Aubreville et al. [27]	2017	Automatic diagnosis of OSCC	CLE image7894	Department of Oral and Maxillofacial Surgery	DNN	A : 88.30 AUC : 0.96 SN : 86.6 SP : 90	Reduced computational complexity	Omitting border not helping in classification
Panigrahi et al. [102]	2019	4layer CNN for feature extraction and classification	Histopathology images-1000	GDC portal	CNN	A : 96.77	No overfitting issues	Data augmentation needs to be employed explicitly
Kirubaba et al. [47]	2021	Morphological features for detection	MRI image 160	Hospital	CNN	A : 99.30	High classification accuracy can be achieved with minimum data	–
Jeyaraj et al. [28]	2019	Develop regression based deep learning algorithm	hyperspectral images-100	BioGPS data portal, TCIA Archive, GDC data set	Partitioned DCNN	A : 91.40 SN : 98 SP : 94.0	Attains high accuracy for complex image	–
Song et al. [35]	2018	Image classification method based on and white light image auto fluorescence	Color image-190		CNN	A : 86.90 SN : 85 SP : 88.7	Useful in community screening	Overfitting problem could arise
Rachit Kumar Gupta et al. [103]	2019	Framework for dysplastic tissue classification	Biopsy image-2688	Indira Gandhi Govt. Dental College and Hospital, Jammu, India	CNN	A : 89.30	Increased accuracy	Need to fine tune deep learning model.
J. Pandia Rajan et al. [43]	2019	locating cancer region in IoT based smart healthcare	PET image-1500	(http://insight-journal.org/midas/)	DCNN	A : 96.80 SN : 92 SP : 97	Useful to extract features from unlabeled data	–

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Table 8 (*continued*).

Publication	Year	Problem addressed	Modality and size of data set	Data set source	Algorithm	Performance Metrics	Advantages	Disadvantages
Yoshiko Ariji et al. [30]	2019	Object detection algorithm for lesion detection	Panoromic images-210		DNN	A : 90 SN : 88.0	Detection and classification sensitivity of radiolucent lesions of the mandible	Need huge amount of labeled data for training
Shashikant Patil et al. [104]	2019	Examine accurate detection	X-ray-120 images	Archived dataset	Adaptive neural network	A : 95 SN : 100 SP : 90 PR : 90.9 F measure : 95.2 MCC 90.45	Better than conventional classifier models	Need to validate with large dataset
Nanditha B R et al. [105]	2020	Detection by combining texture and fractal features	Color images-200	Different medical colleges and hospitals in Karnataka	Back Propagation Neural Network	A : 95 SN : 96 SP : 93.3	Efficient multiclass classification	–
Ross D. UthoffID et al. [29]	2018	Imaging technique for detection on a smartphone platform	170 image pairs	KLE Society's Institute of Dental Sciences	CNN	A : 94.94 SN : 85.50 SP : 88.75	Cost effective	Internet issues and takes excess time
Shetty et al. [106]	2023	Distributed cloud environment model	Histopathological images-1224	Public dataset	Ensemble model with CNN, MLP and SVM	A : 91.40	Improved feature extraction	–

images are analyzed using capsule network as suggested by Santisudha Panigrahi et al. [99] in his research article. The model used for classification is Capsule Network (Capsnet). This is found to be comparatively efficient than CNN. Folmsbee et al. [100] debated that CNN can be better trained using active learning rather than random learning. The model is first trained using CNN and then converted to fully connected CNN by converting 3 dense layers at the last of convolutional layers. Each pixel in an image is labeled as per the result obtained by the classification process.

Anantharaman et al. [33] conferred the detection and segmentation of an object using R-CNN. The architecture used here is U-Net and is designed to provide segmentation for medical images. Mask R-CNN uses region proposal network for identifying the region of interest followed by feature extraction. Anantharaman et al. [101] extended the study to develop a tool. A mouth sore impression is identified using Clarifai's visual algorithm and further classification of images are done using Random forest algorithm.

Aubreville et al. [27] deliberated that the classification is based on texture features and a model is trained during deep neural network. The laser endoscopic images used in this study are splitted into patches and the feature extraction is done by reducing the dimension. Santisudha Panigrahi et al. [102] used four convolutional layers in their proposed model by taking a color image and producing the probable output of whether the image is benign or malignant. Adadelta is used to train the model and cross entropy function to differentiate between two classes. M. Praveena Kirubaba et al.[47] talks about using morphological features for segmentation. Then a CNN is trained to classify whether an image is normal or abnormal and it also differentiate whether it is a mild case or a severe. Jeyaraj et al. [28] deliberated that the feature extraction can be performed using regression Deep CNN after the image preprocessing and segmentation technique. A patch in an image needs to be labeled. A proposed model is compared with the classifiers such as SVM and DBN and found that the proposed model is better in identifying the cancerous region.

Bofan Song et al. [35] used CNN model to train using Imagenet. Along with it he used transfer learning and other regularization method for classifying the cancerous images. Since it used the intra oral imaging device, image preprocessing is done using histogram equalization. Rachit Kumar Gupta et al. [103] also used CNN to perform the multi class classification of cancerous regions. J. Pandia Rajan et al. [43] employed fog computing along with CNN. CNN is used to classify the data in Internet of things (IoT) architecture. The proposed model takes a minimal time for execution and also precisely removes the noise from the data. Yoshiko Ariji et al. [30] presented deep learning based object detection method that identifies the ROI and produces output in textual format. The learning model is implemented using Detectnet. Ross D. UthoffID et al. [29] also presented a object detection method using CNN. It uses an image captured from smartphone that demonstrate the ease of processing data in less time.

Neural network architecture is also used in the detection of cancer lesion in images proposed by Shashikant Patil et al. [104] and Nanditha B R et al. [105]. The neural network classifier works efficiently than any other classifiers. The study proposed by Nanditha B R et al. used textural features along with the fractal features are effective in identifying the oral lesions. Song et al. [107] demonstrated the Bayesian deep learning for image classification to detect an oral cancer. They have proposed it as a reliable classifier with the detection accuracy more than 90%. Lu et al. [108] proposed a oral cancer screening method using deep learning by pipe lining the nucleus detection, selection and classification. Shetty et al. [106] proposed Improved Linear Discriminant Analysis (ILDA), choose the retrieved features that are the most accurate. In order to accurately classify oral cancer, an ensemble of classifiers using SVM, CNN, and MLP will be built. Aquila Exploration Updated with Local Movement (AEULM), a new hybrid optimization model, is used to fine-tune CNN's weights.

The study shows that the Deep learning employs different types of convolutional neural networks that are highly efficient in automating the cancer detection process. It also shows that it provides a excellent results with a classification accuracy greater than 80%. Researchers also used the pretrained models like AlexNet, VGG16, DenseNet [109] to enhance the detection process.

4.3. Fuzzy computing

Fuzzy Computing uses machine intelligence and a mathematical concepts for reasoning. It is used if the input is not precise or contains more distortion or noise. The algorithm that uses fuzzy logic does not require more data and thus need less space. It also does not need much data to perform the reasoning and get results. The use of fuzzy systems along with machine learning technique provides a good detection accuracy. Fuzzy rules and consensus are applied for oral cancer assessment [115].

In this study, we have considered six research articles listed in Table 9 for analyzing the use of fuzzy computing in oral cancer detection.

The Sona et al. [34] proposed a hybrid approach for segmentation, classification and decision making by employing the fuzzy clustering technique for the automatic recognition of oral lesions. It has used fuzzy aggregation operators for decision making by providing a detection accuracy of 92.74%. He proposed a Dental diagnosis system which helps in diagnosing oral cancer and other dental diseases. Vasantha

Table 9
Summary of fuzzy computing techniques in the oral cancer detection.

Publication	Year	Problem addressed	Modality and size of data set	Data set source	Algorithm	Performance metrics	Advantages	Disadvantages
Sona et al. [34]	2017	Hybrid approach of segmentation, classification and decision making	X-ray-87 images	Hanoi Medical University	semi-supervised fuzzy clustering	A : 92.74% MSE : 0.0804 MAE : 0.0804	Autonomous recognition systems	Computational speed is less compared to other segmentation techniques
Kavitha et al. [110]	2020	Prediction from hybrid algorithm	Data Set-161 instances	Mahatma Gandhi Postgraduate Institute of Dental Sciences, Pondicherry	Fuzzy-based decision tree algorithm	A : 90% R : 95 SP : 83 PR : 91	Can handle large dataset	Decision is made only on whether the patient consumed tobacco
Chakraborty et al. [111]	2016	Detection using Bilateral Texture Features	IR images-81	Dr. R. Ahmed Dental College & Hospital (RADCH), Kolkata	fuzzy k-means clustering	A : 86.12%	Texture features supported by sophisticated classifiers	Can be used only for prescreening
Chakraborty et al. [112]	2016	classification using Infrared thermal imaging	IR camera images-94	Dr. R. Ahmed Dental College & Hospital (RADCH), Kolkata	k-means and fuzzy k-means	A : 96:2% and 97:6%	Cost effective imaging	Not robust because of small dataset
Anuradha.K et al. [113]	2018	develop a tool based on histological features to help experts	Histological image-123	Surya Dental Clinic, Coimbatore.	Fuzzy Cognitive Map and Support Vector Machine	A : 92.10%	Simple implementation and easy to handle	Number of iterations required to train the model is more
Anuradha.K et al. [114]	2017	Active Hebbian Learning (AHL) to enhance FCM grading for detection	histopathological images-123	Surya Dental Clinic, Coimbatore.	Active Hebbian Learning (AHL) and SVM	A : 89.47%–90.58%	Allows asynchronous decision making process	Feature extraction method is not used

Table 10
Summary of data mining techniques in the oral cancer detection.

Publication	Year	Problem addressed	Modality and size of data set	Data set source	Algorithm	Performance metrics	Advantages	Disadvantages
Sharma et al. [116]	2017	Classification and association data mining techniques	Data-1,025 patients	Tertiary Care Hospitals of Pune, Maharashtra, India	Apriori algorithm	A : 80 SN : 87.67 SP : 69.46 BCR : 74.05 PR : 63.53 R : 86.67 AUC-ROC : 0.821 PPV : 62.86 NPV : 88.17	Management system is designed to assist the practitioners	–
Sharma et al. [117]	2015	Identification and risk assessment	Data-1,025 patients	Tertiary Care Hospitals of Pune, Maharashtra, India	Bayes optimal classification	A : 99.02 SN : 99.35 SP : 98.01 BCR : 98.68 PR : 99.35 R : 99.35 AUC-ROC : 0.9974 PPV : 99.35 NPV : 98.01	Faster to train and more accurate	Slower in classifying new cases and requires more memory space to store the model
Choudhury et al. [39]	2016	GUI based Interface for detection	Data-524 instances	Hospital	MLP RBFN SLA	A : MLP –99.82 RBFN-99.78 SLA-93.46%	Fastest algorithm to build	–
Wan-Ting Tseng et al. [31]	2015	Data mining techniques to analyze pat cases	Data-673 patient	Medical center in Southern Taiwan	ANN, Decision trees, K-means	A : ANN-93.8967 Decision trees-95.7746% K-means-67.6056%	Helps physicians in decision making	limited data
N.Anitha et al. [118]	2018	To extract information and converting it to a proper structure	Data set-10 set	Hospital	Genetic based ID3 classification algorithm	A : 100	Optimal result	–
Mohamad et al. [119]	2019	Investigation of classification imbalance	Data set-27 attributes	Hospital Universiti Sains Malaysia (HUSM) in Kelantan	SMOTE and Random Under sampling	A : 97 to 98%	Misclassification problem is resolved	Cost sensitivity not considered

Kavitha et al. [110] uses the fuzzy based decision tree algorithm considering people with a tobacco influence. This algorithm is efficient in identifying and predicting an oral cancer and could be validated by comparing it with the Bayesian networks. Chakraborty et al. [111] has done an extensive work with infrared thermal imaging. Textural features are proved to be extremely helpful in clustering that encouraged oral cancer detection using textural features supported by classifying models. They have extended this work by developing a framework that analyzes temperature distribution on human face that greatly improves the accuracy by 10%. Anuradha.K et al. [113] implemented a simple tool that can help clinicians as it is easy to use and provides a good accuracy. They have incorporated Fuzzy cognitive map along with Active Hebbian learning that provides a grading in identifying the tumors. This method mimics the decision making ability of humans and thus it is helpful in detecting the cancer.

Fuzzy computing uses several features like textural, histological features and uses various hybrid approaches in detecting an oral cancer. From the survey, it is evident that the detection accuracy is fairly high in fuzzy based algorithms and proved to be a feasible method in the cancer detection.

Table 11
Summary of genetic algorithms in the oral cancer detection.

Publication	Year	Problem addressed	Modality and size of data set	Data set source	Algorithm	Performance metric	Advantages	Disadvantages
Kourou et al. [120]	2016	time series gene expression data in order to predict	Genetic data-45,015 expression	NeoMark project	Dynamic Bayesian Networks	A: 81.80 ROC : 0.892	Can derive better knowledge regarding recurrence	Missing data is not handled properly
Nguyen et al. [121]	2014	genetic-algorithm-based mathematical approach for detection	Genetic data-23 patients	NeoMark project	gene regulatory network (GRN), probabilistic Boolean networks (PBNs)	A : 81.80%	Prevents to cause cancer cells from cancer causing gene.	Could be resorted because of obstacles
Kalantzak et al. [122]	2014	Analyzing gene network for assessing oral cancer	Genetic data-86 samples	Anderson Cancer Center	GRN	A : 82%	Provides steady state solutions	General in justifying genetic association
Warnke-Sommer et al. [123]	2017	Using bacterial distributions and gene data for detection	microbiome swabs	NCBI-SRA	SVM	A : 87%	Creating useful diagnostic tool using meta genomics	Data set is relatively small
Kourou et al. [124]	2015	formulate gene interaction network from oral cancer	Genomic data-23 patients	NeoMark project	Significance Analysis of Micro arrays (SAM)	A : 79%	Optimal gene network structures	Does not produce robust results
Kourou et al. [125]	2016	OC recurrence prediction	Genetic data-45,015 expression	NeoMark project	Dynamic Bayesian Networks	A : 79%	Able to find relationship between genes	False positive data needs to be validated
Mei Sze Tan et al. [126]	2016	OC survival prediction using genetic programming	Genetic data-31 cases	Malaysia Oral Cancer Database and Tissue Bank System	Genetic programming	A : 83.87% AUC-ROC : 0.83 RMSE :0.4160	Select the features with high correlation	Need to focus on the correlation among the biological features

4.4. Data mining techniques

Data mining is a process of extracting a useful information from the large data sets. It is useful in identifying the patterns in the attributes, that is helpful in decision making. Data mining techniques are useful in designing a framework along with other AI techniques. It uses a data mining tools like DTREG and Weka to build classification models and association rules respectively. Table 10 shows the research articles using data mining techniques to detect oral cancer.

Sharma et al. [116,117] has done a major work using data mining tools in order to provide a framework to detect and prevent the oral cancer. Since they are using the probabilistic model, it not only helps in diagnosing the cancer but also helps in identifying the stage and thereby increases the survivability chances. Tanupriya Choudhury et al. [39] used a various data mining algorithms that are fast to build to obtain an ideal accuracy. Wan-Ting Tseng et al. proposed a method that uses data mining methods that are extremely helpful for the doctors to make their treatment plan. N.Anitha et al. [118] proposed a new algorithm that is efficient in identifying the oral cancer from the given data set.

They have not only used oral cancer data but also different other data sets to validate the model. Mumtazimah Mohamad et al. [119] proposed a system that handles the irrelevant data and therefore solves the problem of misclassification that in turn helps in detecting the oral cancer accurately. In our study we have observed that data mining techniques are helpful in not only detecting the cancer but also has the capability to prevent it by providing the insights in the data [127,128]. MLP and ANN are the most sought algorithms with data mining techniques.

4.5. Genetic algorithms

Genetic algorithm is a part of evolutionary algorithm that uses the idea of genetics and natural selection. It is heuristic algorithm or greedy algorithm that intelligently exploits the previous data to provide better performance. Genetic algorithms uses different operators to choose attributes to provide preference to the import attributes. It uses a genomic data for the detection of oral cancer. Table 11 shows the research articles that used genetic algorithms to detect an oral cancer.

The another reason for the occurrence of oral cancer apart from excessive tobacco or alcohol usage is the damage that happens in the genetic structure. The genomic data can be used to detect the occurrence of oral cancer [129]. The expression of large number of genes are observed using DNA microarray [130]. It is very helpful in finding the pre-cancerous cells. The use of genetic algorithms gives an efficient to way to work on genomic data to identify the cancer.

Kourou et al. [120,125,131] has done an exemplary work in three of their research article using gene expression. A good number of gene expression is collected and analyzed using different algorithms. A gene expression is deferentially expressed and used Reactome tools to carry out the pathway enrichment analysis on the available dataset. The risk of OSCC is identified through disrupted pathways. The time series gene data is given to Dynamic Bayesian network to predict the re-occurrence of oral cancer. This gives a mechanism to monitor the gene data and identify the possibility of re occurrence. A same data set is used along with algorithm that efficiently analyzes the microarray and predict the oral cancer. The model is helpful in keeping a track of oral cancer progression and also helpful in monitoring a deterioration in patients' health after a brief improvement. In other research article with same dataset and using Dynamic Bayesian Network the authors are trying to find the relationship between the genes.

Nguyen et al. [121] used the same NeoMark project data with genetic algorithm and a mathematical approach like boolean networks for the early detection of oral cancer. The K means clustering techniques also aids along with gene regulatory network to identify tumor and non tumor cancer cells. Kalantzak et al. [122] developed a network framework that provides the essential information about genetic structure in the different stages of oral cancer. The Principal Components (PC) and Kool Desktop Environment (KDE) is used to get network structure from the gene data. The KDE and PC could able to identify genetic interactions in blood constructed network up to 86% and 66% respectively. Mei Sze Tan et al. [126] proposed a model that uses genetic programming to automatically select the feature subsets that would potentially affect the oral cancer prognosis. Further the SVM and Logistic Regression are used to check the capability of genetic programming to classify the oral cancer. Genetic programming provides an efficient mechanism not only to detect an oral cancer but it can also be used to monitor in re-occurrence of oral cancer. GRN is proved to be providing a better detection accuracy.

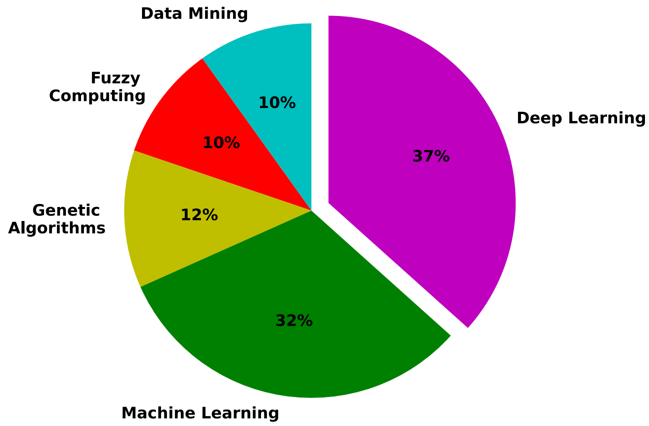

Fig. 5. Analysis of Artificial Intelligence techniques used in Oral Cancer Detection.

Table 12
Highest accuracy achieved by the algorithms.

Algorithms	Highest accuracy achieved in the survey (%)
SVM	100
AdaBoost	95
Multi Layer Perceptron(MLP)	94.1
Gaussian Mixture Model (GMM) classifiers	94.1
Random forest	90
Decision tree	99.4
Logistic regression	100
k-nearest neighbor	92
Classification and regression tree (CART)	83.8
Softmax Discriminant Classifier (SDC)	97.29
Hybrid ABCPSO Classifier	100
BLDA Classifier	83.16
Deep Neural Networks	96
AO+WHO optimization model	92.17
Alexnet	97.66
Faster RCNN	88
3D CNN	79
Fully Convolutional Neural Network	75
Binary CNN	81
CNN	99.3
Capsule Network	97.35
Active Learning	96.44
Mask R-CNN	74.4
Partitioned DCNN	91.4
Adaptive neural network	95
Back Propagation Neural Network	95
Semi supervised fuzzy clustering	92.74
Fuzzy based decision tree algorithm	90
Fuzzy k-means clustering	97.6
Fuzzy Cognitive Map	92.1
Active Hebbian Learning (AHL)	90.58
Apriori algorithm	80
Bayes optimal classification	80
Radial Basis Function Networks	99.78
Simple Logistic	93.46
Artificial neural network	93.89
Genetic based ID3 classification algorithm	100
Dynamic Bayesian Networks	81.8
Gene regulatory network (GRN)	82
Probabilistic Boolean networks (PBNs)	81.8
Significance Analysis of Microarrays (SAM)	79

5. Performance analysis

In this section, the analysis is performed on the various artificial intelligence methods for the early identification of oral cancer. From the Fig. 5, our data clearly shows that deep learning is frequently utilized for oral cancer diagnosis. Most of the recent work is based on the deep learning algorithms as it handles the image data well and also provides a good detection accuracy. Machine learning techniques also is employed when there is a limited data available and performed well. Fuzzy computing and data mining does not show promising results in the oral cancer detection. Genetic algorithms are useful for the detection and re-occurrence of cancer but it does not show any recent advancements.

The extensive range of algorithms are used for the oral cancer detection. Table 12 shows the highest accuracy achieved by the algorithm in the survey. From the table it is evident that the artificial intelligence algorithms provides a good detection accuracy of oral cancer. Fig. 6 shows much employed artificial intelligence algorithms used by the researchers. The support vector machine is found to be the most used classification technique with the highest accuracy in the survey. Algorithms like, random forest, decision trees, logistic regression also are found to be useful providing the excellent detection accuracy. The neural networks are found to be the much liked algorithms for the researchers as this is employed in many articles. The CNN and its variations are much used to deliver the best results and used in the recent study.

6. Conclusion and discussion

This study discussed the various techniques to detect an oral cancer at an early stage. It has given an insight of the different types of inputs that are used for an oral cancer detection **(RQ1)**. It is observed that the histopathology images are much used and also helpful in analyzing and providing the accurate results. It also presented different image processing steps like image enhancement, segmentation, feature extraction and classification methods to detect oral cancer. A complete collection of different AI techniques are presented with different algorithms **(RQ2)** like deep learning, machine learning, data mining, genetic algorithms and fuzzy computing. The advantages and disadvantages of all the algorithms used in the study is analyzed. The important AI technique used in recent articles is the deep learning algorithms and it also provides the best detection accuracy that is above 90% and also reduced error rate **(RQ3),(RQ4)**. One of the important point noticed in the study is the limited availability of data. So an attempt is made to provide the details such as the size of the data and source of data. An important performance parameter such as accuracy of detecting an oral cancer is specified for all the research articles. Around 60% of the research articles referred in this survey are implemented using MATLAB tool and remaining are implemented using Python, java, data mining tools such as WEKA3.7.9,DTREG **(RQ5)**. To summarize, artificial intelligence techniques provide a better result as the detection accuracy is above 90% in most of the methods. This is extremely helpful in the medical field which can provide the results with much lesser time as other medical procedures take a significant time. The researchers can collaborate with doctors to strengthen the way the data needs to be represented. This helps in providing fast and more accurate results and avoid misclassification. This in turn helps the doctors to start the treatment without any delay. This is the main advantage for the early detection of the cancer that can increase the survivability rate of the patients. Another advantage of using AI technique is that it is cost effective. As the medical procedures like scanning and biopsy involves more cost, the computer algorithms can provide a result with an image taken from a mobile phone. In this way, technology can be considered as a boon in the medical field and can greatly help to save peoples' life. Apart from these AI techniques, Natural language Processing (NLP) is another AI technique that needs to be explored to extract data from

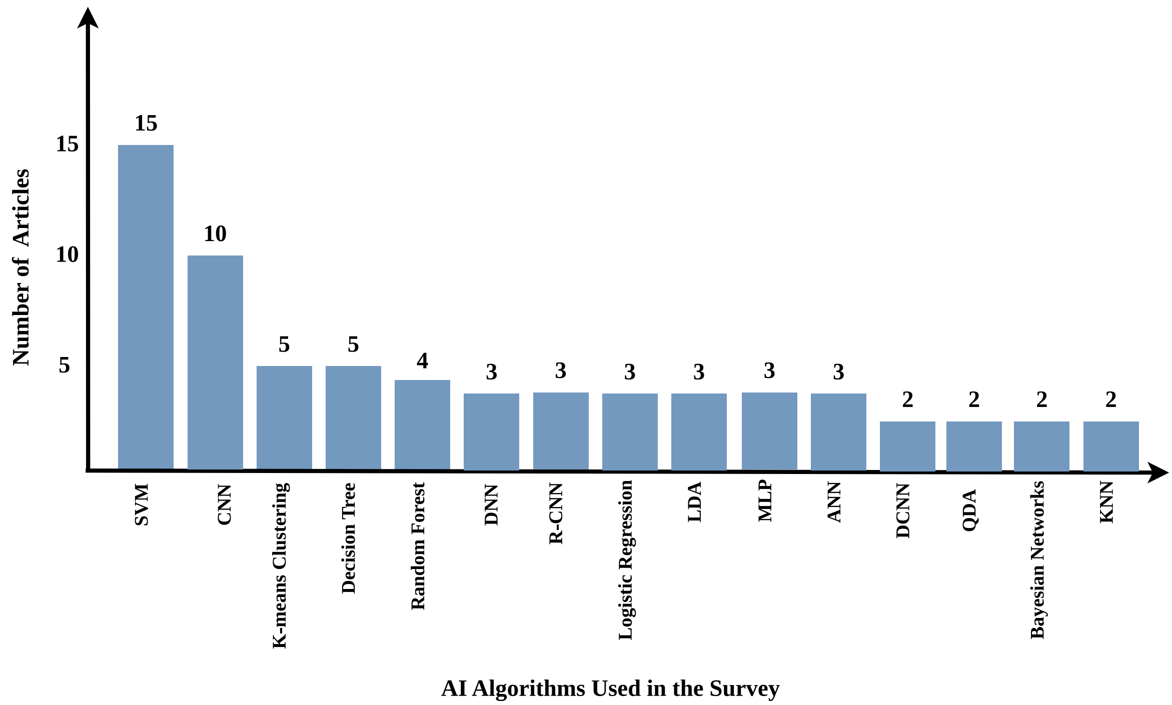

Fig. 6. Artificial Intelligence algorithms used in the survey.

pathology reports, clinical notes, electronic health records, and medical literature. These textual data can be used to find pertinent information on cancer, such as risk factors, symptoms, or treatment alternatives. Swarm-based algorithms can assist in integrating various types of data and extracting valuable information, providing a multi-modal solution for the identification of oral cancer.

Following are some of the issues and challenges identified during the survey **(RQ6)**

- **Limited Dataset**: It is observed in the study that the dataset used for the study is limited. So the augmentation techniques are used to enhance the dataset. Some articles used public dataset and used the data from the hospitals. The annotation and labeling with the experts involved in the study helps in improving the performance.
- **Misclassification** : Even though accuracy is high in most of the algorithms, there is a problem with false positive and false negatives that could degrade the performance of the model.
- **Patch detection** : The identification of a affected area in an image is still an issue remains an issue even with machine learning and deep learning environment.
- **Multimodal Solutions** : For model training, researchers typically employ a single type of data modality. It may not be possible to capture all the relevant information, so the researchers can utilize additional data modalities to record every relevant aspect. This helps to reduce misclassification also.
- **Diagnoses in real time** : After reviewing the literature, it was discovered that very few researchers had suggested a model for real-time oral cancer diagnosis. Significant computational complexity and personal oversight were required to deploy in real time.

Declaration of competing interest

The authors certify that they have NO Affiliations with or involvement in any organization or entity with any financial interest, or non-financial interest in the subject matter or materials discussed in this manuscript.

Data availability

Data will be made available on request.

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