A Systematic Study of Deep Learning Algorithms in Oral Squamous Cell Carcinoma: Current State, Clinical Issues, and Potential Scenarios

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Abstract.

Cancer is an aggressive illness with a limited median lifetime. Recurrence and mortality rates are high during the recovery phase, which can cause the process to be lengthy and costly. Preventing cancer detection in its early stages and improving patient prognosis predictions are important for improving patient survival. As a result of advances in mathematics and data engineering, the precision of quantitative techniques used to determine disease prognosis has increased significantly, and numerous scientists have been motivated to employ these techniques over the years. Cancer prediction accuracy has also improved because of advances in AI especially Machine Learning (ML) and Deep Learning (DL) algorithms. This article discusses the advantages of AI in cancer detection and prognosis after reviewing the literature. A subtype of oral epithelial cancer is known as OSCC. Despite their high mortality rates, even basic screening methods for OSCC are frequently insufficiently specific, and as a result, the disease is usually discovered after it has already spread widely. The percentage of OSCCs that are diagnosed early and have a precise treatment strategy is significantly higher than the percentage of OSCCs that are not diagnosed until later in the course of the disease and do not have a precise treatment strategy. In vivo cell structure analysis can be done using the confocal laser Endomicroscopy (CLE). Studies that used in-situ ultrastructural imaging of OSCC show a bright future for that technology. The objective of this review is to research and discuss existing data on oral cancer detection early in patients.

Keywords. Oral Squamous Cell Carcinoma, Deep learning, Image Classification, Regularization technique.

1. INTRODUCTION

A tumour that starts in the squamous cells or mucous membranes of the skin, called squamous cell carcinoma is one of the type of cancer. There are about 1.3 million new cancer cases in every year in the head and neck as a result of the malignant transformation of these cells. Tissue from an oral cavity tumour will be examined to assign a score. Oral Submucous Fibrosis (OSF) diagnosis using machine learning algorithms is feasible, but no study has been proposed to date testing multi-class grading of oral squamous cell carcinoma (OSCC). Instead of identifying biopsy images for OSCC that show multi-class characteristics, in particular, would assist in reliable prognosis and multi-modal treatment protocols for patients with oral cancer, thus lowering pathologists' clinical workload. Based on this understanding, this survey is planning to use Broder's histological classification scheme to rate OSCC. A promising technology for medical image processing has appeared in the area of artificial intelligence, known as deep learning, which is built using layered neural networks. It has been demonstrated to be comparable to seasoned diagnosticians in terms of diagnostic accuracy. The ACS, CDC, and NAACR work each year to keep their constituents aware of cancer prevalence. This year's thesis discusses both the truth of human papillomavirus cancer and the importance of HPV vaccination. The CDC and the NCI provided data on cancer incidence and death, while the NCI provided data on cancer mortality. a long-term perspective (from 1975/1992 to 2009) and a medium- and short-term perspective (from 2000 to 2009) on the age-adjusted prevalence and death rates for all cancers combined According to national statistics, the Papanicola test coverage rate was greater than 50% in 2008 and 40% in 2010. Between 2000 and 2009, mortality rates for all cancers decreased by 1.5 per cent a year for men and women alike. Incidence rose for men but not for women. The prevalence of two HPV-related tumours, as well as many others, doubled (eg, liver, kidney, thyroid). [1-3]

1.1 HIGHLIGHTS

- Biopsy pictures of the more common oral squamous cell carcinoma were studied (OSCC) using several existing articles.
- A novel CNN based deep learning methodology is suggested for OSCC multi- class cell type classification.
- A transfer learning strategy is also used, with four potential pre-trained models.
- The classification accuracy will be more when we choose a DL based algorithm for the earlier

diagnosis of OSCCcancer.

2. LITERATURE SURVEY

Deep learning is another machine learning subtype that is prone to hierarchical concept formation that needs unique layers of representation to allow more complex concepts to be built on top of. Labelled data is a prerequisite for machine learning algorithms since complex queries that need a lot of processing power to resolve are not feasible. Larger size than one might expect, where it is really needed, is in various real-world scenarios. This review provides a brief review of deep learning algorithms that are the most commonly used today.

Hu, L, et.al, [4] Authors discussed the acetic acid visual inspection of the cervix, but this method cannot be replicated or checked. The aim of this study was to develop a machine learning algorithm that could detect cervical pre-cancer and cancer by "blindly" looking at images. Multiple approaches to test for cervical cancer, as well as a finding of pre- cancerous lesions, were used to monitor a group of 9406 women aged 18 to 94 in the Guanacaste region of Costa Rica for seven years (1993–2000). To find the origins of these tumours, which had been present for 18 years, a tumour registry linkage was performed. Using Faster R-CNN, a deep learning-based approach uses two models based on Automated Visual Evaluation Algorithm and cervix locator, the training and validation were conducted on digitised cervical images of screening photographs captured with a fixed-focus camera (“cervicography”). The prediction score (0-1) generated can be assigned a sensitivity (how good the prediction is) and a precision (how accurate the prediction is).

Kourou, K,et al, [5], the authors presented a summary of recent machine learning methods used in cancer progression modelling. The predictive models presented here are built on Supervised Machine Learning (SML) Models also the more number of diiferent input features and data samples. With the rising pattern of using machine learning approaches in cancer science, we've compiled a list of the most recent papers that use these strategies to model cancer risk or patient outcomes. M. Aubreville et al. [6] explore how, using CLE recordings, authors have implemented and validated. Patch probability fusion is used in a unique automated technique for OSCC diagnosis. Textural feature-based machine learning techniques, such as LBP, GLCM, or LHS, are compared to the current state of the art in terms of the current state of the art in textural feature-based machine learning approaches. For this study, CLE image sequences (7894 images) from the four different places in the oral cavity, as well as the OSCC lesion, were collected from patients diagnosed with OSCC. The new approach outperforms the state of the art in CLE image detection, with a region under the curve (AUC) of 0.96 and a mean accuracy of 88.3per cent (sensitivity 86.6 %, specificity 90 %). N. Das et al. [7] designed a test that utilised the Alexnet, VGG-16, VGG, and ResNet pre-trained deep CNN models to determine the optimal model for our classification problem. Although the Resnet-50 model achieved the highest accuracy of 92.15 per cent, the findings demonstrate that the proposed CNN system outperformed other models and achieved a 97.5 per cent accuracy. This investigation established that the proposed multi-class grading scheme should be used to diagnose OSCC. Huang, S.et.al, [8], authors look at how AI can help with cancer detection and prognosis, focusing on its unparalleled precision, which is much better than that of general predictive oncology applications. We also see how these approaches are helping to advance the sector. Finally, the advantages and disadvantages of using AI in clinical settings are addressed. As a result, this essay offers a fresh outlook on how AI will aid in cancer detection and prognosis, as well as seek to improve human health in the future.

Bur, A. M, et.al [9], authors suggested that when opposed to approaches based on DOI, machine learning increases estimation of pathologic nodal metastasis in patients with clinical T1-2N0 OCSCC. An improved predictive algorithm such as the decision Forest algorithm is required to make sure that that the patients having occult nodal disease get proper treatment while excluding the expense and morbidity of neck dissection in the affected patients who do not have pathologic nodal disease. Yan, H., et.al, [10] Being able to identify squamous cell carcinoma is crucial for surgical care based on fibre Raman spectroscopy and deep learning, this thesis proposed a TSCC-classifying system of convolutional neural networks (CNN). -The first step was to obtain 24 Raman spectra from 12 TSCCs from 12 patients' Results reveal large differences between TSCC non-tumorous tissue to have a range of 700– 1800 cm. A CNN algorithm was applied to spectra to retrieve the nonlinear features. As a final point, the derived features are used to classify TSCC with a. The findings revealed the sensitivity and specificity of 99.07% and 95.37% for CNN's model. As well, testing with TSCC shows our system outperformed current methods. Thus, Raman spectroscopy offers a valuable method for intraoperative assessment of the margins of resection of oral tongue squamous cell carcinoma.

Woolgar, J. A, et.al [11], this paper covers the potential prognostic significance of histopathological characteristics specific to the primary tumour and the lymph nodes. It is also covered briefly in addition Information on the histopathology is supplied with mention of the probable pitfalls. Special emphasis is often placed on the importance of the relationship between the pathologist and the methodologist, histopathology examination phases, and correct recording of results. Santisudha Panigrahi, et.al, [12], authors have proposed an automated computer-aided network called capsule network for oral cancer classification. The dynamic routing strategy used in the capsule network achieved high valiant for the affine changes of the augmented oral dataset using rotation. The capsule network's capability to transform the dataset such as pose, view, orientation changes achieved more appropriate for the histopathological analysis of the oral cancer dataset which makes it robust for the early prediction of oral cancer. The model thus generated is evaluated using the accuracy, sensitivity, precision, F-score and specificity. The generated produces a cross- validation result of the accuracy of 97.35 and specificity and sensitivity of 96.92% and 97.78%.

As per the authors' statement, Chan, et.al [13], proposed a modern deep convolutional neural network (DCNN) with the integrated feature of a texture map for the detection of ROI in an automated integrated model for the detection of cancerous regions. Using a texture map augmented with multiple patches and fed into the DCNN model as an input, the proposed model has two integrated systems: one for detecting oral cancer using feature extraction based on standard deviation values and another for pinpointing the ROI (Region of Interest) for cancer tumours. Standard deviation values are calculated using a sliding window technique. With wavelet transform, we were able to achieve detection sensitivity and specificity on the order of 0.9687 and 0.7129 on average. Gabor filter can achieve detection sensitivity and specificity as high as 0.9314 and 0.9475 on average. DongWook Kim,et.al, [14], the authors compared the Traditional Hazard based model called COX Proportional Hazard (CPH) model with the Random Survival Forest(RSF) and DeepSurv model (the model based on Deep Learning Algorithm) for the survival prediction to examine the patients with OSCC and their survival rate post operation. DeepSurv produced best result among the three models by measuring Harrell's c-index, in both the test and training for measuring the concordance of predicted and actual survival rate, DeepSurv produces highest prediction accuracy when compared with the other two models with 0.810 and 0.781, followed by RSF (0.770/0.764), and the CPH model (0.756/0.694)

Kouznetsova, V. L, et.al [15], Machine learning models have been developed to analyse the metabolic pathways associated with oral cancer and periodontitis, according to the authors' research. For detecting periodontitis in saliva, separate 10-fold cross-validations confirmed. For detecting periodontitis in saliva, separate 10-fold cross-validations confirmed Gravi metabolomic pathways data mining, AI and deep learning approaches such as logistic regression and stochastic gradient descent Oral and periodontitis classifications were shown to be substantially more accurate using neural networks, logistic regression, and stochastic gradient cross-separation. The deep Neural Network (DNN) with the Tensor Flow software had the best results. The accuracy for the prediction of the model was 0.978 % while the methods that didn't include Deep Learning (DL) achieved similar results, albeit much less accurate results.

Paderno, A.,et. al, [16], Completely convoluted neural networks (FCN) are useful in the field of head and neck oncology, since the endoscopic inspection is a necessary aspect of treatment, and in monitoring the effects of cancer on the upper-digest tract. . Semantic segmentation of oral cavity and oropharynx squamous cell carcinomas was tested using FCNN-based algorithms in this study (OP).Two videos were pulled from the institution's tertiary endoscopic video repository that features the combination of NBI and OP interventions. The dataset referred to in the OC had 110 images, while the OP had 116 images. three different types of FCNs (U- a-U-Net, U-Net 3, and ResNet) For the gold-standard assessment, FCNs' success was assessed across all tested networks and compared to the manual annotation. Kim, Y., et.al,[17], In The Cancer Genome Atlas, ORCA data that is publicly available has been filtered using CIBERSORT profiles of ORCA data to create binary risk groups that cluster based on measurement scores and survival patterns for those groups (TCGA). In 16 of the 22 TIL fractions, clinically significant variations were seen in the different classes. TIL fraction patterns are used to train a DNN classifier. Additionally, this internally validated classifier was used on an ORCA dataset from the International Cancer Genome Consortium's data portal to forecast patient survival patterns. Seven genes were found to exhibit significantly different expression within the two risk classes. TILs also played a critical role in the tumour microenvironment; thus, it has piqued the interest of researchers to use a novel deep-learning tool to assist in cancer prognosis.

Yuan, Y, et.al [18] to study multiple machine learning algorithms for prediction of oral tongue metastasis of squamous cell texture on preoperative imaging. 116 individuals with OTSNC and Elective Neck Dissection were surgically removed (END). From T2WI and contrast-enhanced T1 images, the scientists identified 86 texture structures for each patient. The process of shortening included 3 rounds of analysis: reproducibility, collinearity, and knowledge gain advanced algorithm (NN-adv), k-NN, boosting computer (BM), decision tree (DT), perceptron (PT), boosting perceptron (PO), and k-adv SVM (NN). 10-fold cross-validation. Alabi, R. O, et.al [19], After February 2020, authors looked in Ovidline, Scopus, and the IEEE databases for the purpose of diagnostic or predictive uses of OSCC. Only those which applied machine learning models for prognostic and/diagnostic purposes were examined and two experts (O.Y & A.R) used predefined search query parameters to recover papers. The authors followed the Chosen Reporting Substances for Systematic Review and Meta-Analysis (PRIS/meta-Meta). The authors used the Prediction of Bias in Study Assessor for estimating the probability of bias (PROBAST) as well.

Song, B. et.al [20], Auto fluorescence and white light photos were used to train a deep learning-driven image identification algorithm in this work. The data from the auto fluorescence and white light images is retrieved, quantified, and combined to feed the deep learning neural networks. For oral cancer categorization, we examined and compared the efficiency of various CNN, transfer learning, and multiple regularization techniques. The findings of our experiments show that deep learning approaches are useful in categorizing the images of dual modal for oral cancer findings. Here the MatConNet, an open-source CNN toolbox is used in the application, here Data Augmentation improves the classification performance and Regularization technique such as weight decay helps in handling the overfitting problem with an average accuracy of 86.7 percent, the 4-fold cross-validation resulted in an 85.0 percent specificity rate with 86.7 percent accuracy, and an overall accuracy rate of 86.7 percent. Folmsbee, J et.al [21], the Authors investigated several strategies for efficiently training convolutional neural networks (CNNs) for tissue organisation using Active Learning than the more traditional Random Learning (RL) in this study (RL). 143 digitized images of hematoxylin and eosin- stained entire oral cavity cancer parts make up our dataset. In the role of using a CNN to classify seven tissue groups such as stroma, tumor, mucosa, keratin pearls, lymphocytes, semen, and history/adipose. Authors equate AL and RL preparation. For a given training data set size, the AL strategy outperforms the RL strategy by an average of 3.26 per cent.

Hinton, G.et.al [22], For several decades, people have been anticipating that the application of artificial intelligence in health care would arrive. At certain points, AI was built on a foundation of rationality: they concluded that wisdom was something you found through the use of patterns and laws of logic. To encourage programmes and visual models to execute the logic of experts, this approach was implemented. The emergence of deep learning recently (as of early 2018) has enabled technology like speech recognition, image processing, and language translation to be applied to nearly a billion different digital activities. This Viewpoint intends to help medical professionals understand the fundamentals of deep learning. Kann, B. H,et.al [23], They show that a convolutional neural network (Dual Net) can teach itself to recognise nodal metastases and ENE, surpassing human doctors in this area. 3D convolutional neural network trained on 2,875 CT-segmentated lymph node samples and evaluated on 131 blinded research samples were used for validation and fine-tuning. The unblinded test set was used to estimate an AOC of 0.91 (95 percent confidence interval: 0.85–0.97). Patients with head and neck cancer may benefit from this treatment method, which is described as an improvement above the existing standard of care.

Lydiatt, W. M, et. al [24] , In this paper, various modifications that took place in the region are examined in order to help the reader get a greater understanding of how the location has changed. This most recent update included some additions, one of which was the implementation of a separate staging algorithm for HPV-related oropharyngeal cancer, which is distinguished from other types of oropharyngeal cancer. Some other changes to the which includes the division of various types of throat cancer into three separate chapters; the removal of skin and Merkel cell carcinomas from a general chapter that covers the entire body; and the distinction of different types of cancerous tumours (T) for skin, oral cavity, and nasal passage. To compile the staging system, the Head and Neck Task Force participants worked in collaboration with colleagues around the world and created a staging approach that is in compliance with the TNM staging paradigm; the system is easy to use and accommodates the discovery of newer staging guidance. Hartenstein, A.et. al [25], deep learning already functions well, and with better data, especially larger blood sample data sets, and greater access to more qualitative information such as DNA/RNA sequence data, the algorithms would be much better.In a contrast-enhanced CT image, CNNs may characterize lymphatic infiltration by PCa on their own. The performance of CNNs is strongly correlated with their physiological backgrounds, and this is something that must be considered when designing imaging-based biomarkers. Mohammed ,T.et.al[26], proposed a model for the selection of best classification model based on the principle of the Hardy-Weinberg principle where the optimization is carried out using the relevant values of barnacles for the production of best offspring for the better optimization process. The best values are adopted to find the classification of complex problem in a minimal complexity [27-32].

The below table shows the combined data taken from the existing survey papers, which shows that the deep learning method gives a more accurate value when compared to other methods.

Author	Method for Predictor Measurement	Exclusion of poor quality Images	Exclusion criteria	Deep LearningTechniques	Transfer Learning Applied	Accuracy /Sensitivity/ Specificity
Hu, L(2019)	cervicography	NR	NR	Faster R-CNN (automated visual evaluation Algorithm)	yes	95
N. Das(2020)	computer-aided diagnosis for oral sub-mucous fibrosis	yes	A history of maxillary sinus surgery, a fracture, or certain tumours	Transfer Learning (Alexnet, VGG- 16, VGG-19 and Resnet-50)	yes	97.5
Song, B(2018)	Dual-modal mobile imaging device	yes	Very Poor image quality or Clear consensus	MatConNet	yes	89
Bur, A. M(2019)	Tumor depth of Invasion(DOI)	Yes	Inconsistent histopathological findings; instances with less than 10 examples in the training set; cases with missing or inadequate images of mucosa	Decision Forest algorithm	no	95.5
Yuan, H(2021)	MRI Texture analysis	yes	Co-occurrence of two anomalies rather than just one is also acceptable.	convolutional neural networks (CNN)	yes	95.37
Yan, H(2018)	Raman spectroscopy	yes	NR	convolutional neural networks (CNN)	yes	96
Kouznetsova, V. L(2021)	saliva metabolites	NR	NR	The independent 10-fold cross-validations of logistic regression and stochastic gradient descent validated their validity.	no	94.2
Kann, B. H(2018)	CT(lymph node extranodal extension (ENE)	yes	Contrast-enhanced CT	DLNN(Five-fold cross validation for the DualNet model)	yes	97
Hartenstein, A.(2020)	(2) a 68Ga-PSMA PET scan with contrast enhancement	yes	PET/CT scan in lobectomy patients with dissection of lymph nodes in the hilar and mediastinum	Visual Geometry Group (VGGNet), random forests	yes	96
Aubreville, M(2017)	Laser endo microscopy images of the oral cavity	yes	Blurred imaged or images with incomplete exposure	patch probability fusion method	no	90

Table i. Classification methods with its accuracy level

3. CONCLUSION

With conventional machine learning, only a few pieces of information are relevant; with advanced machine learning, any function must be studied and interpreted by an expert before a method can be applied. Due to the increase in available hardware like GPU, deep learning is also given a higher precision for classification for most machine learning methods without having to use hand-feed the algorithm. Very few researchers have applied deep learning and machine learning techniques in the field of the question of diagnosing and predicting oral cancer survival rates have been done this year in literature.

The image processing methods used in this study paper are for identifying oral cancer as well as other oral strategies for growth modelling and assessment are seen to be important for using deep learning for early detection of disease imaging and pathological imaging. The researchers note the importance of human diagnosticians' diagnostic capacity, along with moderate agreement This sophisticated ML-based methodology provides many benefits over the existing measures, including reproducibility, objectivity, immediate monitoring (>10 times quicker than clinicians), and adaptability to clinical demands. It was proven that the DL algorithm is accurate for patients with HNSCC.

Based on the observed the hybrid model consisting of various training model using optimization algorithm such as Barnacle Mating Optimization algorithm is used to achieve best accurate results for the classification of various oral lesion to identify the oral cancer at the earlier stage. The performance of the developed model can be calibrated by various metrics such as F1 score, Precision, specificity.

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