Oral Cancer Detection Using Image Analysis

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Abstract - An Automatic Detection of Oral Cancer using Improved Optimization and Deep Learning methods. Oral cancer is a common and difficult malignancy with a high death rate. With 130,000 deaths each year, it is India's fifth most frequent malignancy. There are several diagnostic procedures for oral cancer; however they are restricted in their ability to detect cancer cells accurately. To use a hybrid optimization strategy to remove redundant features and a Deep Learning neural network to identify oral cancer with a high classification rate and a low error rate likelihood. The proposed study presents a novel technique that employs deep transfer learning models to categorise various oral cancer and non-cancer or normal photos. Oral cancer and normal or non-cancer data were first collected in images from histopathologic and real-time datasets, and then pre-processed to clean the data, locate NAN values, and remove noise signals from the images. Furthermore, pre-processed data has been graphically visualised and summarised toaid in the feature extraction process to locate contour features such diameter, extreme left and extreme top points, area, perimeter, epsilon, approximate, width, height, aspect ratio, extent, equivalent, minimum value, maximum value, and position of the minimum and maximum values, extreme rightmost point, extreme bottom point. Later, 75% of the data was divided into a training dataset and 25% was divided into a testing dataset. Finally, classification is carried out with the help of pre-trained models such as VGG16, MobileNetV2, ResNet50, DenseNet, and VGG 19. The photos were initially pre-processed using techniques such as Gaussian blur to remove noisy signals. Then, using morphological processes, features were extracted to form extreme spots on the images, which were then cropped. To achieve the best results, the collected images were input into deep transfer learning models coupled with optimization techniques such as ADAM, SGD, and RMSprop optimizers. The following metrics were utilised to examine the findings: accuracy, loss, RMSE, precision, and AUC. During Using ADAM, RMSprop, and SGD, the hybrid optimization strategies on DenseNet yielded successful results in the validation phase, with 92.41 percent accuracy, 0.70 loss, and RMSE of 0.29.
for the real-time dataset, 92.41 percent, 0.30 loss, and 0.09 for non-cancerous images derived from the histopathologic, and accuracy of 95.41 percent, loss of 0.10, and RMSE 0.03 for oral cancer images.

Keywords: OCSCC, RMSE, VGG19, AI, RMSprop, ADAM, ML, AUC.

I. INTRODUCTION

Oral cancer is a significant public health concern, with a high global incidence and mortality rate. Over the past decade, the incidence of various cancers has increased significantly, particularly in the mouth, tongue, tonsils, and esophagus, with a startling 60% increase[1]. Cancer is a disease caused by an uncontrolled division of abnormal cells in a body part. In all types of cancer, some of the body's cells begin to expand into nearby tissues and divide unabated. Since the human body is composed of trillions of cells, cancer can begin practically anywhere.. Men over the age of 50 are at the highest risk of developing this disease, and they are twice as likely as women to be affected [2] Normally, human cells grow and divide to form new cells as the body needs them Cells die and are replaced by new ones when they age or sustain injury. The results showed that the DenseNet could be optimized using the Hybrid optimization technique (ADAM+RMSprop+SGD), with good results obtained: 92.41 percent accuracy, loss of 0.70 and RMSE 0.29 for a real-time dataset; 95.41 percent accuracy, loss of 0.10 and RMSE 0.03 for images of oral cancer; and 92.41 percent accuracy, loss of 0.30 and 0.09 for non-cancerous images from Further study is needed to investigate the effectiveness of artificial intelligence for multiclass categorization of oral mucosal lesions utilizing a larger dataset and more instances of challenging lesion kinds in order to make significant improvements to current models. But when cancer arises, this well-organized process falters. As the abnormalities in cells increase,
Many cancers form solid tumours which are masses of tissue. Cancers of the blood, such as leukaemias, generally do not form solid tumours.

1.1 Oral Cancer

Oral cancer starts in the cells of the mouth. A cancerous (malignant) tumour is a group of cancer cells that can grow into and destroy nearby tissue. It can also spread (metastasize) to other parts of the body[3]. The most common place where oral cancer spreads are the lymph nodes in the neck. Oral cancer may also call AS oral cavity cancer or mouth cancer. Cells in the mouth sometimes change and do not grow or behave normally. These changes can lead to non-cancerous (benign) tumors such as warts and fibroids. Changes in the cells of the mouth can also cause precancerous conditions. This means that the abnormal cells are not yet cancerous, but there is a chance that they could become cancerous if left untreated. The most common precancerous conditions in the mouth are leukoplakia and erythroplakia.But in some cases, changes in the cells of the mouth can cause oral cancer. The mouth is covered with a lining called the buccal mucosa (mucosa). The lining of the oral cavity is made up of squamous cells called squamous epithelium. Oral cancer most often begins in these flat, thin squamous cells. This type of cancer is called squamous cell carcinoma of the mouth.

1.1.1. Types of Oral Cancer

Oral cancers include cancers of the:
• Lips
• Tongue
• Inner lining of the cheek
• Gums
• Mouth Cancer
• Hard and soft palate

1.2 Mouth Cancer

Mouth cancer, also known as oral cancer, is where a tumour develops in the lining of the mouth. It may be on the surface of the tongue, the inside of the cheeks, the roof of the mouth (palate), or the lips or gums. Tumours can also develop in the glands that produce saliva, the tonsils at the back of the mouth, and the part of the throat connecting mouth to windpipe (pharynx). However, these are less common [4].

Symptoms of Mouth Cancer
• A lip or mouth sore that doesn't heal
• A white or reddish patch on the inside of mouth
• Loose teeth
• A growth or lump inside your mouth
• Mouth pain
• Ear pain
• Difficult or painful swallowing

1.3 Structure of Human Mouth

The Human mouth begins at the border between the skin and the lips. The roof of the mouth is formed by the hard palate and the soft palate. Mouth leads to the oropharynx (the middle part of the pharynx) and the soft palate separates the mouth from the nasopharynx (the upper part of the pharynx). The inner surface of the cheeks forms the sides of the mouth. The tongue takes up most of the floor of the mouth (the lowest part of the mouth). The mouth can be divided into specific areas, which includes:

• The Lips
• The Soft Palate
• The Tonsils
• The Tongue
• The Uvula
• The Floor of The Mouth
• The Inner Lining of The Cheeks (Buccal Mucosa)
• The Upper Jawbone (Maxilla) And Hard Palate (The Bony Part at the front of the roof of the Mouth formed by part of the upper jawbone) 4
• The Gums And Alveolar Ridge (The Ridge-Like Border Of The Jaws That Contains the sockets of the Teeth)
• The Teeth
• The Lower Jawbone (Mandible)

1.3 Diagnosing Techniques for Oral Cancer

Barium Swallow: - A Barium Swallow test may show irregularities in the larynx, pharynx, mouth and surrounding areas, and may often detect small, early oral tumours[5].

Biopsy: - An oral tissue biopsy is the first step in diagnosing mouth cancer. During the biopsy, surgeon removes a small amount of abnormal tissue from the area where mouth cancer is suspected. Biopsy can confirm an oral cancer diagnosis. The styles of biopsies usually used for diagnosing oral cancers are:

Incisional Biopsy: A small piece of tissue is reduce from an odd-looking place. If the peculiar location is easily accessed, the pattern may be taken at doctor's workplace. If the tumour is deeper within the mouth or throat, the biopsy can also want to be finished in an running room, with wellknown anaesthesia administered to save you ache.
Exfoliative cytology: A suspicious vicinity is lightly scraped to gather a pattern of cells. These cells are placed on a tumbler slide and stained with dye, so they may be without difficulty regarded under a microscope. If any cells seem odd, a deeper biopsy might be completed.

1.4 Stages of Oral Cancer

Doctors assign a stage doctor will assign a stage to cancer after physical exam and the initial results from patient's oral tissue biopsy or imaging tests. The stage may be adjusted if one has additional tests. There are five stages of mouth cancer, starting at zero and going up to four. (They are represented by the Roman numerals I, II, III, and IV.

2. LITERATURE REVIEW

In the framework of the current study, many researchers conducted a thorough literature review. Few findings have been discussed in this work. Chang et al. [6] proposed a predictive strategy for oral cancer prediction based on clinicopathologic and genomic indicators that used a mix of feature selection and machine learning methodologies. Given the selected features of drink, invasion, and p63, the

hybrid model of Relief F-GA-ANFIS produced the best accuracy (accuracy = 93.81 percent, AUC = 0.90). The results showed that using a mix of clinicopathologic and genetic indicators improves prognosis accuracy.

Kourou et al. [7] discussed the fundamentals of machine learning and how they might be used to predict and prognostic cancer. The researcher highlights recent studies and focuses on the construction of predictive models employing supervised machine learning approaches and classification algorithms to forecast valid illness outcomes. Based on the findings, the integration of multidimensional heterogeneous data, in combination with the use of various methodologies for feature selection and classification, might give promising inference tools in the cancer area.

Mohd et al. [8] discussed that to generate the highest accuracy, it is important to reduce and select most related features. The researchers investigate data reduction methods that are applied in the diagnosis of Oral Cancer primary stage using machine learning classification methods. The researcher studies the integrated diagnostic model between preprocessing phases and hybrid FS method to diagnose OC primary stage and demonstrated an increase in classification accuracy. It shows highest classification accuracy with 14 optimal features from a set of 25 features. The author trained four classification algorithms, Updatable Naïve Bayes, Multilayer Perceptron, K-Nearest Neighbors and Support Vector Machine using optimal feature subset. It has been found that the classifier accuracy enhanced by application of Feature Selection methods in comparison to the classifier accuracy without Feature Selection.

Youssefl et al. [9] suggested that Facial and Oral Cancer Tracker (FOCT) a new platform can automatically classify images based on their content. It gives them text annotation and assist surgeons in decisions regarding new cases by supplying visually similar past cases. This tool can also guide diagnostic, treatment, management and monitoring oral most cancers via assessment of lengthy-term consequences in similar instances.This application is based on a web interface, able to classify suspicious regions. To analyze the user's information demand and retrieve target images more correctly, a machine learning solution based on support vector machines and user relevance feedback was also proposed by the researcher. While manual categorization and search by text annotation performed poorly in terms of diagnostics, the CBIR-based technique, in which the physician interacts with the system while inspecting patches and determining the appropriate verified diagnosis, could be useful in practical practice.

Rahman et al. [10] used histological slides for analyzing abnormality based on textural features present in squamous cell carcinoma. Textural features are extracted from biopsy images containing normal and malignant cells using histogram and grey-level cooccurrence matrix techniques. Researcher used linear support vector machine classifier for automated diagnosis of the oral cancer, which gives 100% accuracy. The texture features of the images were considered for performing the classification. The approaches that were used for feature extraction are GLCM (gray-level co-occurrence matrix) and histogram techniques.

3.METHODOLOGY

3.1 Research Design

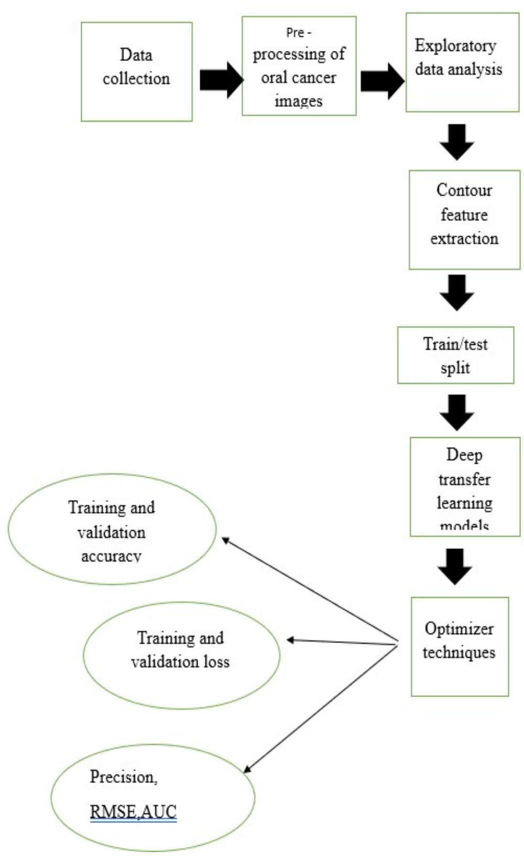
Research refers to a systematic method of consisting of problem, formulating a hypothesis, collecting the data, analyzing the data, and reaching at Positive conclusion both in the shape of solution in the direction of the worried problem or in sure generalization for a few theoretical components. The present study is descriptive and experimental as it aims to study the relationship between selected variables. It is therefore desirable that research design should be methodologically prepared and it depends on research purpose. This chapter explain the various tools and technique of research that was followed to obtain the specific objectives of the study.

3.2 Methodology steps

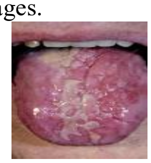
The problem chosen for the current thesis study was solved by following the methodological procedures outlined below in a sequential order. Real-time and histopathologic data image to be used as an input has been chosen. The images of oral cancer were pre-processed. In which data loading and cleaning, as well as the removal of NAN values and noise signals, are performed.

(i) Furthermore, pre-processed information has been graphically visualized and summarization of oral cancer and non-most cancers snap shots to resource in function extraction to extract contour features including location, perimeter, epsilon, approx., width, peak, element ratio, volume, equivalent, minimum price, most price, minimal cost location, most price location, diameter, excessive leftmost point, intense topmost point, intense rightmost factor, extreme backside point to locate the acute points.The train-test split technique was used for evaluating the performance of a machine learning algorithm. Classification is performed using a pre-trained model such as VGG16, MobileNetV2, ResNet50, DenseNet and VGG 19. Various optimizer strategies have also been utilized to optimize the results, such as ADAM, SGD, and RMSprop, which are then assessed using accuracy, loss, RMSE, precision, and AUC.

1.Framework of proposed system



3.3 Implementation flow details
3.3.1 Input Image
The Histopathologic Image was obtained from the Kaggle Dataset [11], which contains 2494 normal images and 2698 images affected by oral cancer, as well as real-time images, which contain 44 normal images and 87 oral cancer affected images.


Cancer Dataset Images

3..3.2 Pre-Processing
Pre-processing is the process of improving a data image by removing undesired distortions and enhancing some image attributes that are crucial for further image processing. There are three main processes in image pre-processing.

- Data Loading and Cleaning
- Removal of NAN values
- Remove Noise Signals

Data loading and Cleaning
The first step is to import the libraries that will be required by the programme. Initially, Opencv, and Imutlis libraries were used to pre-process various oral cancer and non-cancer images A library is essentially a collection of modules that can be called and used, and data cleaning is done after data loading, which involves fixing or eliminating incorrect, corrupted, incorrectly formatted, duplicate, or incomplete data from a dataset. When combining various data sources, there are numerous possibilities for data to be duplicated or mislabeled. Even if the data is correct, the results and algorithms are untrustworthy if the data is incorrect. There is no one-size-fits-all strategy to prescribing the specific phases in the data cleaning process because the methodologies will differ from dataset to dataset. However, it is vital to build a template for the data cleaning operation so that one can be certain that are performing it right each time.
Removal of NAN values
NAN values are those that are not a number. The rows or columns with null values can be deleted to deal with the missing values. If more than half of the rows in a column are null, the column can be dropped entirely. The rows with null values in one or more columns can also be removed[12]. The NAN values are removed in this process.
Removal of Noise Signals: - After the removal of NAN values the Noise is removed from the images i.e noise from a signal. The noise removal algorithms reduce or remove the visibility of noise by smoothing the entire image leaving areas near contrast boundaries.
3.3.3Exploratory Data Analysis
After pre-processing the images from both the datasets, the information was summed and presented graphically using the histogram. R represents red, G refers to green, and B is blue in RGB histograms for both oral cancer and non-cancer or normal pictures. The histogram view shows the intensity distribution of photographs, which also includes the quantitative value of the number of pixels used to depict each intensity value[13]. Similarly, histogram equalization broadens the intensity range to map one intensity distribution to another, resulting in an equitable distribution of intensity values. To put it another way, it disperses the most common intensity levels. As a result, the image's contrast is improved.
3.3.4Contour Feature Extraction
Features were extracted in two ways using contour features and the target highlighting approach. Contour features or morphological features are returned as properties of pre-processed images from both datasets[14]. Researcher used equation to compute various parameters from input photos, which encompass vicinity, perimeter, epsilon, approx, width, peak, aspect ratio, quantity, equivalent, minimum value, maximum fee, minimum cost location, maximum fee vicinity, diameter, extreme leftmost factor, severe topmost factor, excessive rightmost factor, the intense backside point of each oral cancer and non-most cancers or normal pictures.
3.3.5 Train-Test Split
It can be used for classification or regressionproblems and can be used for any supervised learning algorithm. The procedure involves taking a dataset and dividing it into two subsets. 75% of the data was separated into a training dataset, and 25% was split into a testing dataset.
3.3.6 Deep Transfer Learning Model
Here different Deep Tranfer learning models were used like VGG16, MobileNetV2, ResNet50, DenseNet, and VGG 19 for classification.
VGG16 and VGG19

VGG stands for the Visual Geometry Group. VGG16 is made up of 33 kernel-sized filters that are used in a consecutive order (11 and 5 in the first and second convolutional layers, respectively). The input for VGG is a 224*244 RGB image[15]. Over a million images from the ImageNet database were used to train the VGG-19 Convolutional Neural Network. The network contains 19 layers and is capable of identifying photos from a variety of categories. The main idea behind the VGG architectures is to keep the convolution size small and constant while creating a very deep network.

ResNet50

Thearchitecture of ResNet50 is separated into four parts. The network may accept a picture with a height, width, and channel width that are all multiples of 32. The network may accept a picture with a height, width, and channel width that are all multiples of 32. With a kernel size of 7*7 and 3* 3, each ResNet architecture performs initial convolution and max-pooling[16]. In the 34-layer net, each 2-layer block is replaced by this 3-layer bottleneck block, resulting in a 50-layer ResNet.

3.3.7 Optimization Techniques

After Deep mastering version’s optimization approach is used. Optimization algorithms may be grouped into those who use derivatives and people that don't. There are many different types of optimization algorithms that can be used for continuous function optimization problems, and perhaps just as many ways to group and summarize them[17]. The following optimization technique are used:

ADAM

ADAM is a deep learning model training algorithm that replaces stochastic gradient descent. Adam combines the great capabilities of the AdaGrad and RMSProp algorithms to create an optimization algorithm for noisy issues with sparse gradients. The Adam optimizer combines momentum and root suggest rectangular propagation, gradient descent techniques. By thinking of the 'exponentially weighted common' of the gradients, this algorithm is used to speed up the gradient descent algorithm [18]. Using averages accelerates the algorithm's convergence to the minima. By taking into account the 'exponentially weighted average' of the gradients, the momentum algorithm is used to speed up the gradient descent algorithm. Using averages accelerates the algorithm's convergence to the minima. A Root Mean Square Propagation Algorithm (RMSprop) is a Gradient Descent-based Learning Algorithm that combines Adagrad and Adadelta methods.

RMSprop

Root Mean Squared Propagation, or RMSProp, is a variation of gradient descent and the AdaGrad version of gradient descent that adapts the step size for each parameter using a decaying average of partial gradients[19]. The vertical oscillations are limited by the RMSprop optimizer. As a result, one can increase the learning rate, allowing the algorithm to take larger horizontal steps and converge faster. The difference between RMSprop and gradient descent is the method of calculating the gradients.

SGD

Stochastic Gradient Descent refers to a system or process with a random probability distribution. As a end result, Stochastic Gradient Descent makes use of some randomly decided on samples in place of the complete information set for every generation. Stochastic gradient descent is a famous and extensively used method in Machine Learning [20]. In large-scale, sparse machine learning problems like text classification and natural language processing, stochastic gradient descent has proven to be successful. In stochastic gradient descent, one can calculate the gradient using a single data point or example and update the weights with each iteration.

4 Conclusion

Oral cancer is a disease that has recently become more common throughout the world, yet it is still poorly understood. OSCC (Oral Squamous Cell Carcinoma) is induced by a variety of circumstances, including extrinsic factors like nicotine and alcohol, as well as intrinsic factors like hunger and anemias. OPMD (Oculopharyngeal Muscular Dystrophy) is linked to or precedes several OSCCs, including leukoplakia. As a result, in medical practice, correct classification of oral lesions is critical. Using breakthroughs in deep learning, multiple deep transfer learning algorithms have been used to predict non-cancer or normal and oral cancer images. The five deep transfer learning models and three optimization algorithms utilized were discussed. The real-time dataset includes 44 noncancer photographs and 87 oral cancer images, as well as 2494 normal shots from the histopathologic dataset and 2698 oral impacted images from the real-time dataset. Most of the oral cancer research was published after 2014, and it was focused in Asia, which has the world's highest rates of lip and mouth cancer. As a result, this research provides the most comprehensive solution to the problem of categorizing normal and oral cancer photographs. The experimental results demonstrated a significant relationship between model prediction performance and experimental data, indicating that DenseNet is useful for the prediction of oral cancer and non-cancerous images. To the best of the knowledge, no scientific effort has contributed to the gifts, as previously stated. Artificial intelligence can be an innovative and practical technique for too early diagnosis of oral cancer. Various deep learning algorithms were tried to discover which one performed the best on a histopathologic and real-time dataset. The five transfer learning models used in this work were ResNet50, VGG16, VGG19, MobileNetV2, and DenseNet. The findings were obtained using three optimizers, including ADAM, RMSprop, SGD, and their hybrid method. The data set comprises a variety of photographs from two separate datasets that may categorize oral images as impacted or unaffected. The performance of five different algorithms when paired with three different optimization methodologies is compared in this study. After training, these algorithms had been examined using the last 0.25 or 25% of the check dataset with zero.Seventy five or 75% of the input facts. The accuracy, loss, precision, root suggest rectangular blunders and area below a curve of the strategies had been in comparison for training and validation trying out.

5 Result and Discussion

The results showed that applying the Hybrid optimization approach (ADAM+RMSprop+SGD) to the DenseNet produced powerful results, with an accuracy of 92.Forty one percent, lack of zero.70, and RMSE 0.29 for a actual-time dataset, accuracy 95.Forty one percent, loss zero.10, and RMSE 0.03 for oral cancer snap shots, and accuracy 92.Forty one percentage, loss zero.30, and zero.09 for non-cancerous photos taken from the histopathologic dataset.

Input	Accuracy				
	ResNet 50+(ADAM +RMS Prop + SGD)	Mobile NetV2 +(ADAM +RMS Prop +SGD)	VGG 16+ (ADAM +RMS Prop+ SGD)	VGG 19+(ADAM +RMS Prop +SGD)	Dense Net+(ADAM +RMS Prop +SGD)
Real-time dataset	90.26	91.42	90.48	91.56	92.41
Oral Cancer images from histo-pathologic dataset	91.26	92.48	91.48	92.65	95.41
Non-cancerous image from histo-pathologic dataset	90.48	91.42	90.34	90.48	92.41

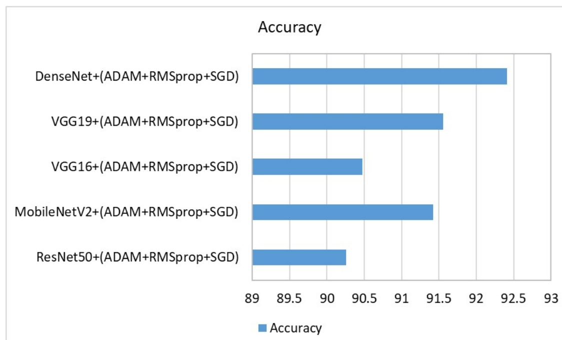


Figure 2 Accuracy analysis for real-time dataset

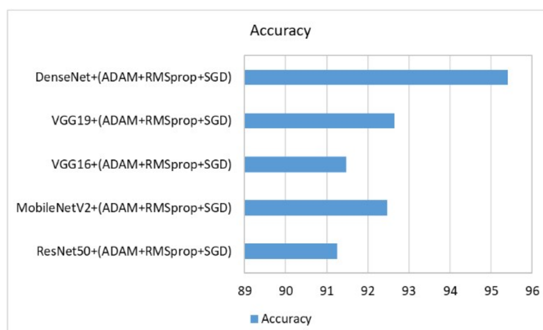


Figure 3 Accuracy analysis for oral cancer images

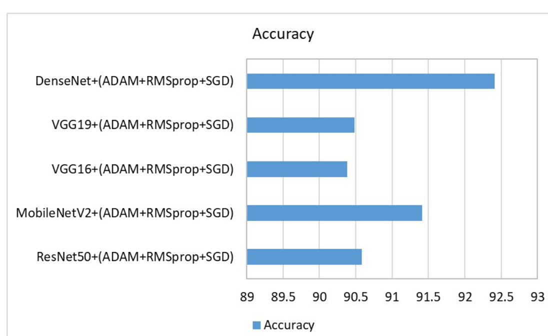


Figure 4 Accuracy analysis for non-cancerous images

6 Future work

In destiny paintings, it'll be viable to gather extra pics for enriching the dataset and to enhance the accuracy of the fashions the usage of specific optimization strategies of excellent-tuning and augmentation. The most important purpose can be enforcing a semantic segmentation for deciding on lesion region from an input image to improvise accuracy results of the fashions.

REFERENCES

[1.] E.Hanetal, Model identification of proton-exchange membrane fuel cells based on a hybrid convolutional neural network and extreme learning machine optimized by improved honey badger algorithm.Sustainable Energy Technol. Assess.(2022)
[2.] Computer-assisted medical image classification for early diagnosis of oral cancer employing deep learning algorithm, 3 January 2019
[3.] Oral Cancer-TSC Wong, D Wiesenfeld First published: 25 March 2018
Statement on mouth cancer diagnosis and prevention,C. Scully & J. Kirby , 10 January 2014
[4.] Analysis of Dysphagia Patterns Using a Modified Barium Swallowing Test Following Treatment of Head and Neck Cancer, So-Yoon Lee, Bo Hwan Kim, Young Hak Park, 17 November 2014
[5.] H. Leng,A new wind power prediction method based on ridgelet transforms, hybrid feature selection and closed-loop forecasting,Adv. Eng. Inf.(2018)
[6.] S. Xu, Y. Liu, W. Hu, C. Zhang, C. Liu, Y. Zong, S. Chen, Y. Lu, L. Yang, E. Y. K. Ng, Y. Wang, and Y. Wang, ''An early diagnosis of oral cancer based on three-dimensional convolutional neural networks,'' IEEE Access, vol. 7, pp. 158603–158611(2019)
[7.] C.Nagarajan and M.Madheswaran - 'Experimental verification and stability state space analysis of CLL-T Series Parallel Resonan Converter' - Journal of ELECTRICAL ENGINEERING, Vol.63 (6), pp.365-372, Dec.2012.
[8.] C.Nagarajan and M.Madheswaran - 'Performance Analysis of LCL-T Resonant Converter with Fuzzy/PID Using State Space Analysis'- Springer, Electrical Engineering, Vol.93 (3), pp.167-178, September 2011.
[9.] C.Nagarajan and M.Madheswaran - 'Stability Analysis of Series Parallel Resonant Converter with Fuzzy Logic Controller Using State Space Techniques'- Taylor & Francis, Electric Power Components and Systems, Vol.39 (8), pp.780-793, May 2011.
[10.] C.Nagarajan and M.Madheswaran - 'Experimental Study and steady state stability analysis of CLL-T Series Parallel Resonant Converter with Fuzzy controller using State Space Analysis'- Iranian Journal of Electrical & Electronic Engineering, Vol.8 (3), pp.259-267, September 2012.
[11.] Nagarajan C., Neelakrishnan G., Akila P., Fathima U., Sneha S. "Performance Analysis and Implementation of 89C51 Controller Based Solar Tracking System with Boost Converter" Journal of VLSI Design Tools & Technology. 2022; 12(2): 34–41p.
[12.] C. Nagarajan, G.Neelakrishnan, R. Janani, S.Maithili, G. Ramya "Investigation on Fault Analysis for Power Transformers Using Adaptive Differential Relay" Asian Journal of Electrical Science, Vol.11 No.1, pp: 1-8, 2022.
[13.] G.Neelakrishnan, K.Anandhakumar, A.Prathap, S.Prakash "Performance Estimation of cascaded h-bridge MLI for HEV using
[14.] SVPWM" Suraj Punj Journal for Multidisciplinary Research, 2021, Volume 11, Issue 4, pp:750-756
[15.] G.Neelakrishnan, S.N.Pruthika, P.T.Shalini, S.Soniya, "Perfromance Investigation of T-Source Inverter fed with Solar Cell" Suraj Punj Journal for Multidisciplinary Research, 2021, Volume 11, Issue 4, pp:744-749
[16.] C.Nagarajan and M.Madheswaran, "Analysis and Simulation of LCL Series Resonant Full Bridge Converter Using PWM Technique
[17.] with Load Independent Operation" has been presented in ICTES'08, a IEEE / IET International Conference organized by M.G.R.University, Chennai.Vol.no.1, pp.190-195, Dec.2007
[18.] M Suganthi, N Ramesh, "Treatment of water using natural zeolite as membrane filter", Journal of Environmental Protection and Ecology, Volume 23, Issue 2, pp: 520-530,2022
[19.] M Suganthi, N Ramesh, CT Sivakumar, K Vidhya, "Physiochemical Analysis of Ground Water used for Domestic needs in the Areabof Perundurai in Erode District", International Research Journal of Multidisciplinary Technovation, pp: 630-635, 2019
[20.] Oral cancer prognosis based on clinicopathologic and genomic markers using a hybrid of feature selection and machine learning methods.Siow-Wee Chang, Sameem Abdul-Kareem, Amir Feisal Merican & Rosnah Binti Zain 31 May (2013)
[21.] Machine learning applications in cancer prognosis and prediction.Konstantina Kourou,a Themis P. Exarchos,a,b Konstantinos P. Exarchos,a Michalis V. Karamouzis,c and Dimitrios I. Fotiadisa,b Nov 15(2014)
[22.] Application and Performance of Artificial Intelligence (AI) in Oral Cancer Diagnosis and Prediction Using Histopathological Images: A Systematic Review.Sanjeev B. Khanagar,Lubna Alkadi,Maryam A. Alghilan, Sara Kalagi,Mohammed Awawdeh, Lalitytha Kumar Bijai, Satish Vishwanathaiah,5 Ali Aldhebaib, and Oinam Gokulchandra Singh , Jun 1(2013)
[23.] A Current Review of Machine Learning and Deep Learning Models in Oral Cancer Diagnosis: Recent Technologies, Open Challenges, and Future Research
[24.] Directionsby Shriniket Dixit,Anant Kumar, and Kathiravan Srinivasan Automatic detection of oral cancer in smartphone-based images using deep learning for early diagnosis.Huiping Lin,a Hanshen Chen,b Luxi Weng,a Jiaqi Shao,a and Jun Lina, Aug 28(2021)
[25.] Textural pattern classification for oral squamous cell carcinoma.T.Y. rahman, l.b. mahanta, c. chakraborty, a.k. das, j.d. sarma, 02 August (2017)
[26.] Analysis of Histopathological Images for Early Diagnosis of Oral Squamous Cell Carcinoma by Hybrid Systems Based on CNN Fusion Features 30 May (2023)
[27.] Exploratory Research Focusing on Oral Cancer Prevention: Challenges of Dealing With Informational and Cognitive Barriers,October 8 (2018)
[28.] Stratified squamous epithelial biopsy image classifier using machine learning and neighborhood feature selection,panelArchana Nawandhar, Navin Kumar b, Veena R c, Lakshmi Yamujala d, Volume 55, January 2020
[29.] Automatic Detection of Oral Squamous Cell Carcinoma from Histopathological Images of Oral Mucosa Using Deep Convolutional Neural Network by Madhusmita Das,Rasmita Dash and Sambit Kumar Mishra 3, 20 January 2023
[30.] An Ensemble Deep Neural Network Approach for Oral Cancer Screening, Nanditha B R, Geetha A, Chandrashekar H S, February 24, 2024
[31.] Deep transfer learning techniques with hybrid optimization in early prediction and diagnosis of different types of oral cancer, 09 May 2022
[32.] Analysis of Deep Learning based Optimization Techniques for Oral Cancer Detection,K J Subha M.Anto Bennet,Gaddam Pranay, Ketham Bharadwaj, Polu Vikram Reddy, 01 August 2023
[33.] Revolutionizing Oral Cancer Detection: An Approach Using Aquila and Gorilla Algorithms Optimized Transfer Learning-Based CNNs, by Mahmoud Badawy , Hossam Magdy Balaha,Ahmed S. Maklad,Abdulqader M. Almars andMostafa A. Elhosseini , 19 October 2023