Artificial Intelligence for Oral Squamous Cell Carcinoma Detection

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AUTHOR BIO

As a 10th-grade high school student with a passion for technology, this individual has already gained significant experience in web and app development, UI and UX, AI/ML, and backend engineering. With a strong interest in research, they have even authored two papers in the field of cancer, demonstrating an impressive level of dedication and skill. Driven by a desire to learn and grow in the field of technology, this student is constantly seeking out new opportunities to challenge themselves and expand their knowledge. Whether working on personal projects or collaborating with others, they approach every task with a high level of enthusiasm and a willingness to explore new ideas and techniques. With a proven track record of success in the technology industry and a deep commitment to learning and growth, this student is poised to make a significant impact in the field of technology in the years to come.

ABSTRACT

This research paper investigates the potential of Artificial Intelligence (AI) techniques for the detection of Oral Squamous Cell Carcinoma (OSCC) using a Histopathological Image Dataset. Three different AI models were trained with varying levels of regularization and dropout layers using TensorFlow, an open-source software library for machine learning. The study found that AI-based techniques can achieve high levels of accuracy in the detection of OSCC, with one of the models achieving an accuracy of almost 90%. The use of regularization and dropout layers was found to improve the accuracy of the models. The results of this research demonstrate the potential of AI in improving the accuracy and speed of cancer detection, which could lead to earlier diagnosis and better treatment outcomes for patients. This research has implications for the development of diagnostic tools in the field of medical image analysis.

INTRODUCTION

The field of medical image analysis has undergone significant advancements in recent years, with the emergence of Artificial Intelligence (AI) techniques providing new avenues for detecting and diagnosing various diseases. Oral Squamous Cell Carcinoma (OSCC), a type of oral cancer that arises from the lining of the mouth and throat, is one such disease where early detection and diagnosis is critical to improving patient outcomes. In this context, this research paper aims to investigate the potential of AI techniques for the detection of OSCC using a Histopathological Image Dataset.

Convolutional Neural Networks (CNNs) have become a popular deep learning architecture for image recognition tasks due to their ability to learn spatial features and classify objects with high accuracy (O'Shea, Nash). CNNs utilize a hierarchical structure of multiple layers, including convolutional layers, pooling layers, and fully connected layers, to extract increasingly complex features from the input image.

Over the years, various studies have been conducted to explore the use of AI in medical image analysis. For instance, Chaunzwa et al. (2021) investigated the use of deep learning algorithms for the classification of lung cancer from CT images, while Ozsahin et al. (2023) explored the potential of AI-based techniques for the detection of breast cancer. While these studies have shown promising results, there is a need for further exploration of AI techniques for the detection and diagnosis of other types of cancer, such as OSCC.
The rationale for this research is to improve the accuracy and speed of OSCC detection and diagnosis, which could lead to earlier intervention and better treatment outcomes for patients. The use of AI in medical image analysis has the potential to address the limitations of traditional methods, such as human interpretation of images, which can be subjective and prone to errors. By using a Histopathological Image Dataset and TensorFlow, an open-source software library for machine learning, this research aims to train and evaluate three different AI models with varying levels of regularization and dropout layers, to determine their efficacy in detecting and classifying OSCC cells.

The hypothesis of this research is that AI-based techniques can achieve high levels of accuracy in the detection of OSCC, with the use of regularization and dropout layers improving the accuracy of the models. This hypothesis is based on prior knowledge and observations in the field of medical image analysis, where studies have shown that AI-based techniques can improve the accuracy and speed of disease detection. The prediction is that the use of AI techniques in detecting OSCC will result in improved accuracy and speed, leading to earlier diagnosis and better treatment outcomes for patients.

The overall objective of this research project is to test the efficacy of AI-based techniques for the detection of OSCC using a Histopathological Image Dataset. The independent variable in this study is the AI technology used, with three different models trained and evaluated. The dependent variable is the accuracy and loss of the models, which will be used to evaluate their efficacy in detecting and classifying OSCC cells.

MATERIALS AND METHODS

Histopathological Image Dataset Preparation

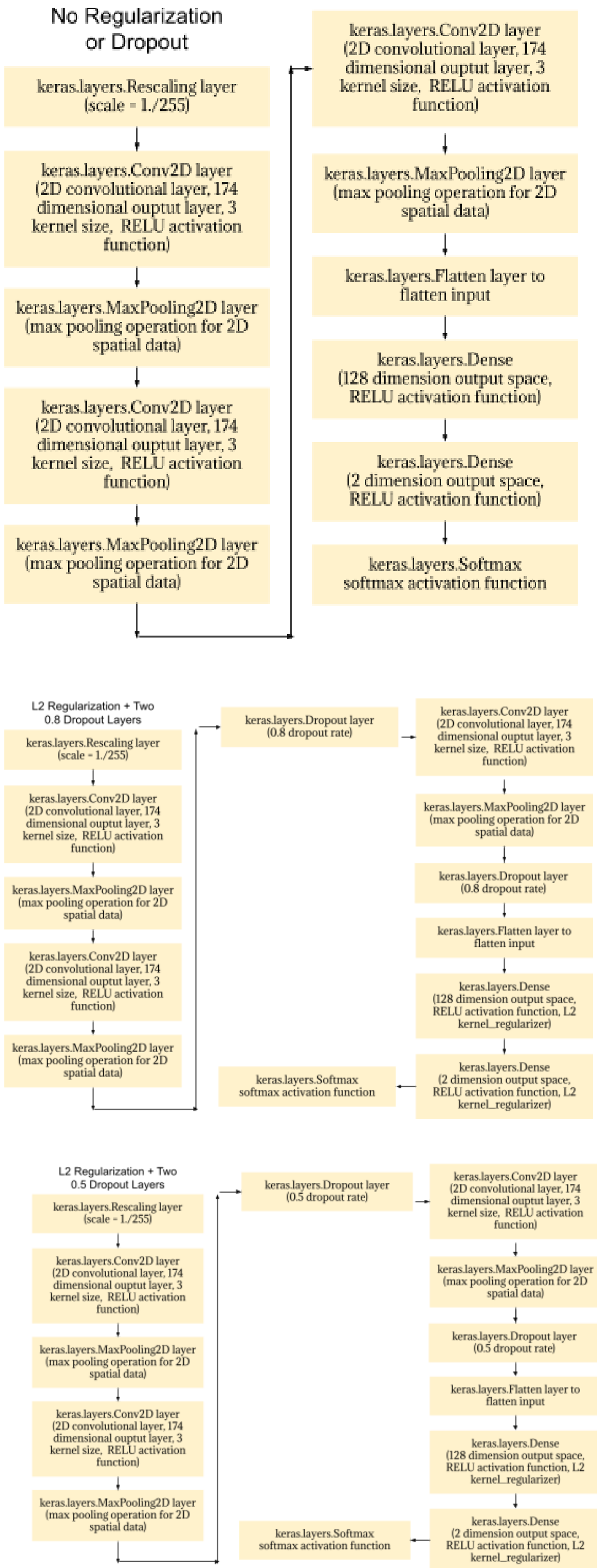
A dataset containing images of Oral Squamous Cell Carcinoma (OSCC) was obtained from a public repository (Rahman). The dataset consisted of images of different magnifications and contained various types of OSCC cells. Data augmentation was performed on this dataset to increase the size of the dataset and improve the accuracy of the models. The augmentation process included rescaling, random flipping, and random cropping. Augmentation was performed on the 400x magnification dataset. This dataset contains 201 Normal Oral Cavity Histopathological (NOCH) images and 495 OSCC images. The data was augmented by adding 36,209 augmented images to the NOCH dataset and 35,002 to the OSCC dataset. This meant that the NOCH dataset had a total of 36,410 images and the OSCC dataset had a total of 35,497 images.

AI Model Training

The choice to develop three different AI models with varying levels of regularization and dropout layers is a significant one for several reasons. Firstly, it allows us to explore the impact of regularization techniques and dropout layers on the model's performance. Regularization methods like L2 regularization help prevent overfitting by adding a penalty term to the loss function based on the magnitudes of the model's weights. Dropout layers, on the other hand, introduce randomness during training by temporarily deactivating a fraction of neurons, reducing co-dependency among them and improving generalization.

The first model, which lacked any regularization or dropout layers, serves as our baseline model. It gives us insight into the model's performance without any regularization or dropout-induced constraints, which can be essential for understanding how these techniques influence the model's behavior. The second model, with L2 regularization and 2 Dropout layers of 0.5, demonstrates a moderate level of regularization and dropout, allowing us to observe the impact of these techniques on mitigating overfitting and model generalization. In contrast, the third model, with L2 regularization and 2 Dropout layers of 0.8, represents a more aggressive application of these techniques. This model's significance lies in showing the potential trade-off between regularization strength and model accuracy. While stronger regularization can enhance generalization, it might also risk underfitting.

Additionally, the hardware specifications of the computer used for training, featuring a 12th Gen Intel(R) Core(TM) i7 - 12650H processor, 32 GB of RAM, and an NVIDIA GeForce RTX 3070 laptop graphics card, play a crucial role in the training process. These high-performance components facilitate faster model convergence and overall efficiency during training, reducing the time and resources required for experimentation. The significance of this hardware setup lies in its ability to support the efficient training of multiple models with various configurations, enabling a comprehensive analysis of the impact of regularization and dropout layers on the AI models' performance.



Evaluation

The trained models were evaluated based on their ability to accurately detect and classify cancerous cells. The evaluation was performed using a separate test dataset that was not used during the training process. The test dataset contained 24 NOCH images and 50 OSCC images. The accuracy and loss were calculated for each model. Each model ran with 100 epochs, which each took around 17 and a half hours. Loss and accuracy curves were graphed. The validation dataset used 75% of the images available and the batch size for these models were 32.

Ethical Considerations

This study used publicly available data, and thus ethical approval was not required. However, all procedures were performed in accordance with the relevant guidelines and regulations.

RESULTS

Figure 4: *Calculated Data Table of Test Accuracy and Loss of Each Group*

	Test Accuracy (%)	Test Loss
No Regularization or Dropout	81.08%	3.4668
L2 Regularization + Two 0.5 Dropout Layers	89.19%	0.7172
L2 Regularization + Two 0.8 Dropout Layers	85.14%	0.5928

Figure 5: Training and Validation Metrics for No Regularization or Dropout

Figure 6: Training and Validation Metrics for L2 Regularization + Two 0.5 Dropout Layers

Figure 7: Training and Validation Metrics for L2 Regularization + Two 0.8 Dropout Layers

DISCUSSION

Summary of Results and Conclusions

The results of this study demonstrate that using regularization and dropout techniques can significantly improve the accuracy of our AI model for detecting oral squamous cell carcinoma. In particular, we found that using L2 regularization and two 0.5 dropout layers resulted in the highest test accuracy of 89.19%, compared to 81.08% without any regularization or dropout, and 85.14% with L2 regularization and two 0.8 dropout layers.

These findings suggest that overfitting was a significant issue in our initial model, and that regularization and dropout techniques were effective in addressing this problem.
Regularization can help prevent overfitting by adding a penalty term to the loss function, which encourages the model to use smaller weights and avoid relying too heavily on any one input feature. Dropout layers work by randomly dropping out some of the neurons during training, which can help prevent co-adaptation of neurons and reduce overfitting.

It is important to note that although L2 regularization and two 0.5 dropout layers resulted in the highest accuracy, the model with L2 regularization and two 0.8 dropout layers still performed better than the model without any regularization or dropout. This suggests that even modest levels of regularization and dropout can be effective in improving the performance of the model.

The results suggest that using regularization and dropout techniques can significantly improve the accuracy of an AI model for detecting oral squamous cell carcinoma. In particular, using L2 regularization and two 0.5 dropout layers resulted in the highest accuracy. These findings have important implications for the development of AI models for medical image analysis, as overfitting is a common challenge in this field. By incorporating these techniques, it may be possible to improve the accuracy and reliability of AI models for detecting cancer and other medical conditions.

Future Studies and Research Impact

The present study provides valuable insights into the use of regularization and dropout techniques for enhancing the accuracy of AI models for oral squamous cell carcinoma detection. However, several avenues for future research can be pursued to build on our findings and to advance the field.

One possible direction for future research is the optimization of the hyperparameters of the regularization and dropout techniques. While we used a fixed set of hyperparameters for L2 regularization and dropout layers, other combinations might lead to higher accuracy. A systematic exploration of the hyperparameter space could help identify the most effective combinations for different types of medical image analysis.

Another potential area of research is the extension of our study to other types of cancer detection. Although our study focused specifically on oral squamous cell carcinoma, similar techniques could be employed for detecting other types of cancer, such as breast or lung cancer. Researchers could use the insights gained from our study to develop more accurate and reliable AI models for a range of medical applications.

Furthermore, our study highlights the potential impact of AI in the field of medical image analysis. By improving the accuracy of AI models for cancer detection, missed diagnoses could be reduced and earlier detection provided for patients. With the continued advancement of AI technology, there may be further opportunities to enhance the accuracy and efficiency of medical image analysis, which could have significant benefits for patients and healthcare providers alike.

ACKNOWLEDGEMENTS

- The Scholar Launch team for providing this opportunity and guidance
- Ramin Ramezani for greatly helping this project and teaching AI/ML concepts
- Michael Powell for assistance and support of this project

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