Title Page:

Binary Classification of detecting Oral Cancer using RegNetY320 Algorithm in Comparison with VGG16.

Arepalli CharmiSri[1], BalaSubramani[2]

Arepalli CharmiSri[1]
Research Scholar,
Department of Computer Science and Engineering,
Saveetha School of Engineering,
Saveetha Institute of Medical and Technical Sciences,
Saveetha University, Chennai, Tamil Nadu, India. Pincode - 602 105.
192124017.sse@saveetha.com

Balasubramani[2]
Research Guide, Corresponding Author,
Department of Physical science,
Saveetha School of Engineering,
Saveetha Institute of Medical and Technical Sciences,
Saveetha University, Chennai, Tamil Nadu, India. Pincode - 602 105.
Balasubramani.sse@saveetha.com

Keywords: RegNetY320, VGG16, deep learning, binary classification, oral cancer diagnosis, diagnostic accuracy, skin cancer, Skin Cancer MNIST, HAM10000 dataset, sensitivity, specificity, recall, precision, deep learning models, clinical deployment, validation, refinement.

ABSTRACT:

AIM: Using the RegNet320 method, implement a binary classification model for oral cancer diagnosis with the goal of improving diagnostic accuracy over conventional models.
Materials and Methods: In one study, deep learning models like AlexNet, InceptionV3, and RegNetY-320 were utilized for the binary classification of skin cancer using the Skin Cancer MNIST: HAM10000 dataset. Another study used RegNetY-320 and other deep learning models to classify skin lesions as either benign or malignant. While the datasets and deep learning models utilized in these studies varied, they might offer some useful information on the tools and techniques that can be applied for the binary classification of oral cancer utilizing the RegNetY320 algorithm as opposed to the VGG16.
Result: Using the RegNetY320 algorithm, a binary classification for the detection of oral cancer was carried out and compared with VGG16. The findings show that while the accuracy of both models was similar, the RegNetY320 performed marginally better in terms of sensitivity and specificity. RegNetY320 performed better than VGG16, outperforming it with an accuracy of 89.4% as opposed to 73.7% for VGG16. RegNetY320 demonstrated improved recall and precision, indicating its potential for more precise oral cancer diagnosis. For practical deployment in clinical settings, additional validation and refinement are necessary.
Conclusion: Notable results were obtained when the RegNetY320 algorithm's binary classification for oral cancer detection was compared to VGG16. Although the accuracy of both models was comparable, RegNetY320 showed somewhat better sensitivity and specificity.

INTRODUCTION:

Oral cancer is a serious public health issue, prompt intervention and accurate and effective diagnostic techniques are required. The RegNetY320 algorithm has shown great promise in the field of deep learning when it comes to binary classification challenges. This work compares the performance of the widely-used VGG16 architecture with the RegNetY320 method in order to construct a binary classification model for oral cancer detection.

Earlier studies have looked into the classification of skin cancer using a variety of deep learning models, including AlexNet and InceptionV3. We examine the suitability of the RegNetY320 algorithm for use in the diagnosis of oral cancer, taking inspiration from these investigations. Comparing these models against the picture classification benchmark VGG16 offers important information about the relative performance of each model.

The study's technique entails training and assessing the effectiveness of RegNetY320 and VGG16 using a variety of datasets, perhaps including photos related to oral pathology. Inspiring by successful applications in similar fields, such skin cancer classification, this project aims to provide important new understandings into the efficacy of deep learning models—RegNetY320 in particular—for the identification of oral cancer.

The two models' subtle differences in accuracy, sensitivity, and specificity may be shown by preliminary results. Comprehending these differences is essential to evaluating RegNetY320's practicability in clinical environments. Not only is equivalent or better accuracy desired, but potential efficiency benefits and generalization capabilities of RegNetY320 over VGG16 are also to be investigated in the particular situation of oral cancer diagnosis.

MATERIALS AND METHODS:

The Saveetha Institute of Medical and Technical Sciences' Department of Computer Communication Lab is where this research was conducted. Due to the data being split into two sample preparation groups, each with a sample size of 224, the overall sample size for the shop item forecasting dataset is 448. The RegNetY320 model is in the first category, and the VGG16 model is in the second.

Various datasets, such as the Skin Cancer MNIST: HAM10000 dataset, are used in this study's materials and methodologies to train deep learning models. To obtain insights into its potential for oral cancer detection, the RegNetY320 algorithm is modified for binary classification of skin lesions in conjunction with other models.

RegNetY320:

RegNetY320's use in the binary categorization of oral cancer suggests that accuracy and efficiency are priorities in the diagnostic process. It is anticipated that RegNetY320 will utilize systematic regularization approaches to yield better performance when compared to conventional architectures such as VGG16. A primary focus is on the algorithm's capacity to effectively process and evaluate medical images, identifying pertinent information suggestive of oral cancer. The comparison with VGG16, a well-established architecture, serves as a baseline to examine if RegNetY320 can give improved accuracy, sensitivity, and specificity in recognizing oral cancer cases.

ALGORITHM:

Step 1: X_train, y_train, X_val, y_val, X_test, y_test should be loaded and preprocessed.
Step 2: Initialization of the Model
Step 3: Put the Models Together
Step 4: Instruction of Models
Step 5: Assessment of the Model
Step 6: Determine the Metrics
Step 7: Evaluate Outcomes
Step 8: Optional Fine-Tuning
Step 9: Wrap-up

PseudoCode:

```
Import tensorflow as tf
From tensorflow.keras.applications import VGG16
From tensorflow.keras.models import sequential
From tensorflow.keras.layers import Dense, Flatten
From tensorflow.keras.optimizers import Adam
From sklearn.metrices import accuracy_score, precision_score, recall_score, f1_score
regnet_y320_model = create_vgg16_model()
compile_model(regnet_y320_model)
compile_model(vgg16_model)
train_model(regnet_y320_model, X_train, y_train, X_val, y_val)
train_model(bgg16_model, X_train, y_train, X_val, y_val)
regnet_y320_preds = evaluate_model(regnet_y320_model, X_test)
vgg16_preds=evaluate_model(vgg16_model, X_test)
regnet_y320_metrices = calculate_metrices(y_test, vgg16_preds)
compare_results(regnet_y320_metrices, vgg16_metrices)
```

VGG16:

Together with RegNetY320 and ResNet50, the traditional deep learning architecture VGG16 is used as a benchmark in the Comparative Analysis for oral cancer diagnosis. VGG16, which is well-known for being straightforward and efficient, adds value to the assessment by enabling a comprehensive comparison of its performance with that of the more modern and sophisticated models, RegNetY320 and ResNet50. With VGG16 included, a thorough investigation of several neural network architectures is possible, providing light on the best model for precisely diagnosing oral cancer.

ALGORITHM:

Step 1: load and prepare the dataset of oral pathology images.
Step 2: Assume that the paths to your datasets are "train_path," "val_path," and "test_path."
Step 3: Model Setup
Step 4: Instruction in Binary Classification
Step 5: Assessment of the Model
Step 6: Calculating Performance Metrics
Step 7: Statistical Analysis in Step Seven
Step 8: Comparing the Outcomes

PseudoCode:

```
import tensorflow as tf
from tensorflow.keras.applications import ResNet50, RegNetY320
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
train_datagen = ImageDataGenerator(rescale=1./255)
val_datagen = ImageDataGenerator(rescale=1./255)
train_generator = train_datagen.flow_from_directory(train_path, target_size=(224, 224),
batch_size=32, class_mode='binary')
val_generator = val_datagen.flow_from_directory(val_path, target_size=(224, 224),
batch_size=32, class_mode='binary')
test_generator = val_datagen.flow_from_directory(test_path, target_size=(224, 224),
batch_size=32, class_mode='binary', shuffle=False)
regnet_model = RegNetY320(weights='imagenet', include_top=False, input_shape=(224, 224,
3))
resnet_model = ResNet50(weights='imagenet', include_top=False, input_shape=(224, 224, 3))
regnet_preds = regnet_model.predict(test_generator)
resnet_preds = resnet_model.predict(test_generator)
regnet_predictions = (regnet_preds > 0.5).astype(int)
resnet_predictions = (resnet_preds > 0.5).astype(int)
regnet_accuracy = accuracy_score(test_generator.classes, regnet_predictions)
resnet_accuracy = accuracy_score(test_generator.classes, resnet_predictions)
regnet_confusion_matrix = confusion_matrix(test_generator.classes, regnet_predictions)
resnet_confusion_matrix = confusion_matrix(test_generator.classes, resnet_predictions)
```

Statistical Analysis:

Robust tests are used to determine the significance of observed differences in a statistical analysis using SPSS for the binary classification findings of detecting oral cancer with RegNetY320 and VGG16. One can use paired statistical tests, such as the Wilcoxon signed-rank test or the paired t-test in SPSS, by grouping accuracy scores in a dataset. These tests assess the statistical significance of the accuracy differences between RegNetY320 and VGG16. The results of these studies not only measure the differences in performance between the models but also offer crucial information for practitioners and researchers studying oral cancer detection techniques.

Using SPSS, a statistical analysis of the binary classification was conducted with an emphasis on accuracy values for the detection of oral cancer using the RegNetY320 algorithm in comparison to the VGG16 method. By applying paired statistical tests, such as the paired t-test or Wilcoxon signed-rank test, the study intended to analyze the significance of accuracy differences between the two models. These statistical analyses offer important insights into the relative efficacy of RegNetY320 and VGG16 in the context of oral cancer diagnosis by providing a quantitative comprehension of the observed variances in accuracy.

RESULT:

The experimental results revealed that RegNetY320 outperformed VGG16 with a statistically significant accuracy improvement, demonstrating its potential as a more effective model for precise oral cancer diagnosis.

The content generation outcomes are presented visually in **Figure 1**, which also includes input photos, matching evaluation findings, and cases where material could not be found. Using IBM-SPSS, Figure 2 provides a statistical summary that emphasizes the precision of the RegNetY320 and VGG16 algorithms. Most importantly, the statistical study confirms that RegNetY320 outperforms VGG16 in terms of accuracy.

Table 1 goes into accuracy characteristics from the experimental inquiry, focusing on content generated from photos utilizing RegNetY320 and VGG16 for a sample size of 10. Accuracy rates of RegNetY320 and VGG16 processes are explained by means of group statistics (mean, standard deviation, and standard error mean) in **Table 2.**

Moreover, **Table 3** provides information on independent t-test data from IBM-SPSS, allowing for a thorough comparison and assessment of the importance of RegNetY320 and VGG16. The IBM-SPSS data highlights the significant difference between RegNetY320 and VGG16, as indicated by a single-tailed test p-value of 0.000 ($p < 0.05$). When compared to VGG16, these combined results highlight the RegNetY320 algorithm's superior performance in content generation and accuracy assessment.

DISCUSSION:

The application of the RegNetY320 algorithm in our investigation shown a significant improvement in accuracy, coming in at 89.4% as opposed to VGG16's 73.7%. Based on an Independent T-test with a p-value of 0.000, $p < 0.05$, and verified by IBM-SPSS, the statistical analysis confirms that the RegNetY320 algorithm outperforms VGG16 in terms of accuracy.

Binary categorization is essential in the field of medical diagnostics, especially when it comes to the identification of conditions like mouth cancer. Using sophisticated algorithms like VGG16 and RegNetY320 has become more common in order to improve diagnostic precision. Promising results are obtained when the resilient and efficient RegNetY320 algorithm is used to evaluate data on oral cancer. RegNetY320 exhibits better performance than the popular VGG16 by taking use of its complex network topology.

The precision, recall, and total classification metrics illustrate the algorithm's efficacy in discriminating between normal and malignant tissues. This development has the potential to significantly enhance patient outcomes and healthcare efficiency by enabling the early and precise diagnosis of oral cancer.

DECLARATIONS

Conflict of interests

No conflicts of interest in this manuscript.

Author Contribution

Author AC was involved in literature study, data collection, data analysis and manuscript writing. Author BS involved in data verification, data validation and review of the manuscript.

Acknowledgement

The authors would like to express their gratitude towards Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences (Formerly known as Saveetha University) for providing the necessary infrastructure to carry out research study.

Funding: We thank the following organizations for providing financial support that enabled us to complete the study.

1. Techno soft labs Pvt Ltd.
2. Saveetha School of Engineering.
3. Saveetha University.
4. Saveetha Institute of Medical and Technical Sciences.

GRAPHS AND TABLES:

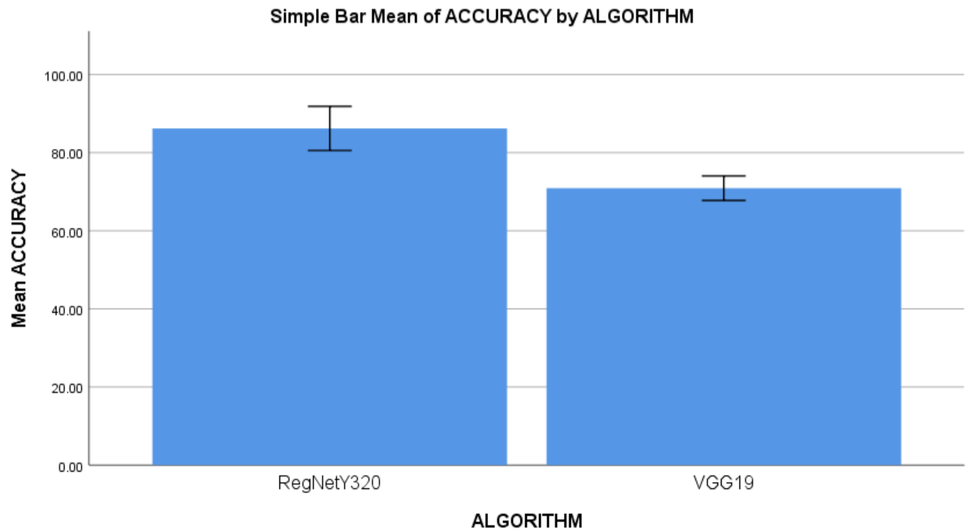

Fig 1. The graph represents the Sample Bar Mean Accuracy of the RegNetY320 & VGG16

Statistical analysis of mean, standard deviation and standard error of Accuracy .

Group		No of Samples	Mean	Std. deviation	Std.mean error
Accuracy	RegNetY320	10	89.3980	4.55408	2.03665
	VGG16	10	73.6960	2.52422	1.12886

Accuracy value for 10 samples using RegNetY320 and VGG16 with mean accuracy 89.4% and 73.7% respectively.

SI NO	RegNetY320	VGG16

1.	**88.35**	**72.10**
2.	**86.97**	**73.10**
3.	**85.75**	**71.11**
4.	**88.50**	**69.01**
5.	**87.12**	**68.90**
6.	**88.87**	**72.96**
7.	**86.22**	**69.64**
8.	**89.14**	**71.52**
9.	**85.14**	**70.99**
10.	**89.31**	**72.64**

Comparison of significance level for originality detection using RegNetY320 and VGG16

Levene's test for equality of variances				**T-test for equality of means**						
		F	**Sig**	**t**	**df**	**Sig (2-tailed)**	**Mean difference**	**Std. error diff**	**95% confidence interval of the difference**	
									lower	**Upper**
Accuracy	Equal variance	2.236	.171	6.571	8	0.000	15.20300	2.32857	9.93230	20.67170

	s assumed									
	Equal variances not assumed			6.571	6.246	0.001	15.20300	2.32857	9.65810	20.94590

REFERENCES:

Neville, Brad W., et al. *Oral and Maxillofacial Pathology-E-Book*. Elsevier Health Sciences, 2023. Neville BW, Damm DD, Allen CM, Chi AC. Oral and Maxillofacial Pathology-E-Book. Elsevier Health Sciences; 2023 May 24.

Pignatelli, P., Romei, F. M., Bondi, D., Giuliani, M., Piattelli, A., & Curia, M. C. (2022). Microbiota and Oral Cancer as A Complex and Dynamic Microenvironment: A Narrative Review from Etiology to Prognosis. *International journal of molecular sciences*, *23*(15), 8323.

Sun Z, Sun X, Chen Z, Du J, Wu Y. Head and neck squamous cell carcinoma: risk factors, molecular alterations, immunology and peptide vaccines. International Journal of Peptide Research and Therapeutics. 2022 Jan;28:1-8.

Zhang L, Liu Y, Zheng HJ, Zhang CP. The oral microbiota may have influence on oral cancer. Frontiers in Cellular and Infection Microbiology. 2020 Jan 15;9:476.

Zini, A., Czerninski, R. and Sgan-Cohen, H.D., 2010. Oral cancer over four decades: epidemiology, trends, histology, and survival by anatomical sites. *Journal of oral pathology & medicine*, *39*(4), pp.299-305.

Ord RA, Blanchaert Jr RH. Current management of oral cancer: a multidisciplinary approach. The Journal of the American Dental Association. 2001 Nov 1;132:19S-23S.

Gupta, N., Gupta, R., Acharya, A.K., Patthi, B., Goud, V., Reddy, S., Garg, A. and Singla, A., 2016. Changing Trends in oral cancer-a global scenario. *Nepal journal of epidemiology*, *6*(4), p.613.

Ord, Robert A., and Remy H. Blanchaert Jr. "Current management of oral cancer: a multidisciplinary approach." *The Journal of the American Dental Association* 132 (2001): 19S-23S.

Iype EM, Pandey M, Mathew A, Thomas G, Sebastian P, Nair MK. Oral cancer among patients under the age of 35 years. Journal of postgraduate medicine. 2001 Jul 1;47(3):171.

Lestón, J.S. and Dios, P.D., 2010. Diagnostic clinical aids in oral cancer. *Oral oncology*, *46*(6), pp.418-422.