

Jinwhan Kim · Brendan Englot ·
Hae-Won Park · Han-Lim Choi ·
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Robot Intelligence Technology and Applications 6

Results from the 9th International
Conference on Robot Intelligence
Technology and Applications

Feature-Aided SMC-PHD Filter for Nonlinear Multi-target Tracking in Cluttered Environments	351
Romain Delabeye, Hyo-Sang Shin, and Gokhan Inalhan	
Hand Gesture and Arm Movement Recognition for Multimodal Control of a 3-DOF Helicopter	363
Ricardo Romero, Patricio J. Cruz, Juan P. Vásquez, Marco Benalcázar, Robin Álvarez, Lorena Barona, and Ángel Leonardo Valdivieso	
Data-Driven Preflight Diagnosis of Hexacopter Actuator Fault Based on Principal Component Analysis of Accelerometer Signals	378
Taegyun Kim and Seungkeun Kim	
The Classification of Oral Squamous Cell Carcinoma (OSCC) by Means of Transfer Learning	386
Ahmad Ridhaudin Abdul Rauf, Wan Hasbullah Mohd Isa, Ismail Mohd Khairuddin, Mohd Azraai Mohd Razman, Mohd Hafiz Arzmi, and Anwar P. P. Abdul Majeed	
The Diagnosis of Diabetic Retinopathy: An Evaluation of Different Classifiers with the Inception V3 Model as a Feature Extractor	392
Farhan Nabil Mohd Noor, Wan Hasbullah Mohd Isa, Ismail Mohd Khairuddin, Mohd Azraai Mohd Razman, Rabi Muazu Musa, Ahmad Fakhri Ab. Nasir, and Anwar P. P. Abdul Majeed	
Cognition, Autonomy and Intelligence	
Deep Learning Based Real-Time Biodiversity Analysis Using Aerial Vehicles	401
Siddhant Panigrahi, Prajwal Maski, and Asokan Thondiyath	
Field Friction Recognition and State Inference in AI Soccer	413
Chansol Hong, Gyeong-Min Lee, Jae-Woo Choi, and Jong-Hwan Kim	
MMH-GGCNN: Multi-Modal Hierarchical Generative Grasping Convolutional Neural Network	422
Sun-Kyung Lee, Hyun Myung, and Jong-Hwan Kim	
s-DRN: Stabilized Developmental Resonance Network	431
In-Ug Yoon, Ue-Hwan Kim, Hyun Myung, and Jong-Hwan Kim	
Comparison of Deep Q-Learning, Q-Learning and SARSA Reinforced Learning for Robot Local Navigation	443
Hafiq Anas, Wee Hong Ong, and Owais Ahmed Malik	



The Classification of Oral Squamous Cell Carcinoma (OSCC) by Means of Transfer Learning

Ahmad Ridhaudhin Abdul Rauf¹, Wan Hasbullah Mohd Isa¹,
Ismail Mohd Khairuddin¹, Mohd Azraai Mohd Razman¹, Mohd Hafiz Arzmi²,
and Anwar P. P. Abdul Majeed^{1,3,4,5,6(✉)}

¹ Innovative Manufacturing, Mechatronics and Sports (iMAMS) Laboratory, Faculty of Manufacturing and Mechatronic Engineering, Universiti Malaysia Pahang, 26600 Pekan, Pahang, Malaysia

amajeed@ump.edu.my

² Cluster of Cancer Research Initiative, International Islamic University Malaysia, 25200 Kuantan, Pahang, Malaysia

³ Centre for Software Development and Integrated Computing, Universiti Malaysia Pahang, 26600 Pekan, Malaysia

⁴ Faculty of Engineering, Technology and Built Environment, UCSI University, Kuala Lumpur Campus, 56000 Cheras, Kuala Lumpur, Malaysia

⁵ EUREKA Robotics Centre, Cardiff School of Technologies, Cardiff Metropolitan University, Cardiff C5 2YB, UK

⁶ School of Robotics, XJTLU Entrepreneur College (Taicang), Xi'an Jiaotong-Liverpool University, Suzhou 215123, P. R. China

Abstract. Patients that are diagnosed with oral cancer has more than an 83% survival chance if it is detected in its early stages. However, through conventional labour-intensive means, only 29% of cases are detected. It is worth mentioning that 90% of oral cancer is Oral Squamous Cell Carcinoma (OSCC) and is often caused by smoking and alcohol consumption. Computer-aided diagnostics could further increase the rate of detection of this form of oral cancer. The present study sought to employ a class of deep learning techniques known as transfer learning. The Inception V3 pre-trained convolutional neural network model is used to extract the features from texture-based images. Consequently, the malignant and benign nature of the cancer is identified from three different machine learning models, i.e., Support Vector Machine (SVM), *k*-Nearest Neighbors (*k*NN) and Random Forest (RF). It was shown from the study that an average of 91% classification accuracy was obtained from the test and validation dataset from the Inception V3-RF pipeline. The outcome of the present study could serve useful in an objective-based automatic diagnostic of OSCC and hence could possibly increase its detection.

Keywords: Oral squamous cell carcinoma · Oral cancer · Transfer learning · InceptionV3 · *k*NN · RF · SVM

1 Introduction

Oral cancer is the world's sixth most frequent occurrence of cancer [1]. According to the World Health Organization, 657,000 new instances of oral cavity and pharyngeal malignancies are diagnosed each year, with more than 330,000 fatalities globally [2]. Oral cancer has an extremely high mortality rate owing to the lack of early detection. Moreover, it is worth noting that amongst the different types of oral cancers, Oral Squamous Cell Carcinoma (OSCC) is the most prevalent type, with more than 90% of oral cancer cases are from this type.

Conventional means of diagnosing by oncologists are somewhat labour intensive, especially for non-developing countries. Hence, researchers have attempted to use computer vision with machine learning techniques to facilitate the diagnosis of such ailment. For instance, Das et al. investigated the use of Convolutional Neural Networks (CNN) in the diagnosis of OSCC, particularly in the detection of keratin pearls [3]. A second stage classification means was used, i.e., Gabor based feature extraction with Random Forest (RF) classifier. It was shown that the method proposed could classify the keratin pearls with a classification accuracy (CA) of 96.88%

Ren et al. employed investigated the efficacy of different machine learning in predicting the histological grade of OSCC from MRI based images [4]. The dataset was collected from the Shanghai Ninth People's Hospital. The RF, Artificial Neural Network (ANN) and Logistic Regression (LR) with and without synthetic minority oversampling technique (SMOTE) were evaluated by considering the 10-fold cross-validation technique. It was shown from the study that the RF classifier with SMOTE could attain a CA of 86.3%.

A 3D CNN model was developed by Xu et al. in diagnosing oral cancer based on CT images [5]. The model was compared with a 2D-based CNN model to classify the oral tumours as benign or malignant. It was demonstrated from the study that the 3D CNN model was better in discriminating the type of cancer in comparison to the 2D CNN model with an average CA of 75.9%

Transfer learning which is a sub-category of deep learning, has gained traction recently, primarily owing to its attractive feature that does not require one to train a model from scratch but leverages on pre-trained CNN models. It has been employed in different applications and has demonstrated appreciable performance [6–10]. Nonetheless, to the best of the authors' knowledge, limited studies have been carried out on its application on OSCC. Therefore, this study attempts at investigating the efficacy of a transfer learning model, i.e., Inception V3, in extracting the relevant features from the skin images prior to its classification on different traditional machine learning models.

2 Methodology

In the present investigation, the images were obtained from a repository provided by Rahman et al. [11]. The images were collected from Ayursundra Healthcare and Bhubaneswar Borooah Cancer Institute from 230 patients. The images were captured by using a Leica DM750 microscope (ICC50 HD Model) at 100 × and 400 × magnifications. In the present study, the second set that contains 201 normal oral cavity images and 495 OSCC images were used. The former set of images were duplicated to have an

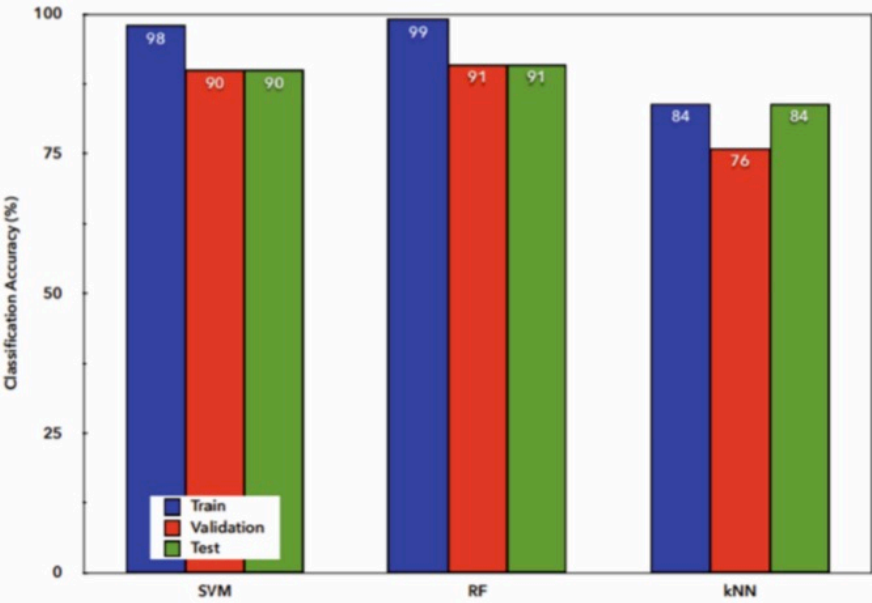


Fig. 2. Classification accuracy of the developed pipelines.

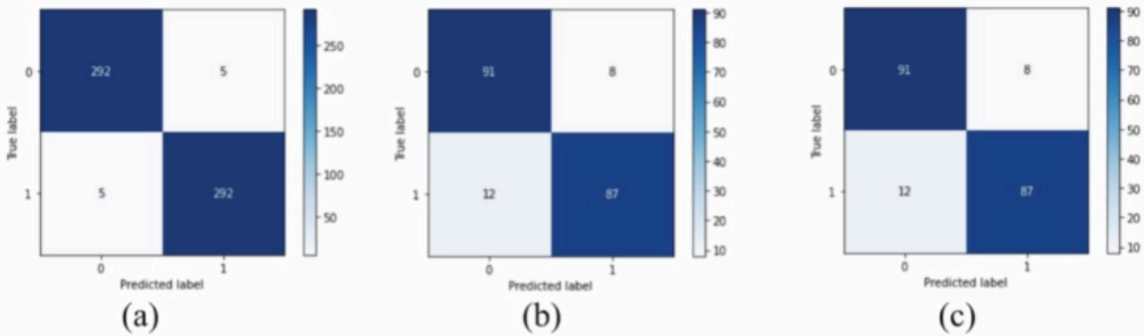


Fig. 3. Confusion matrix for (a) Training (b) Validation (c) Testing of the InceptionV3-SVM model.

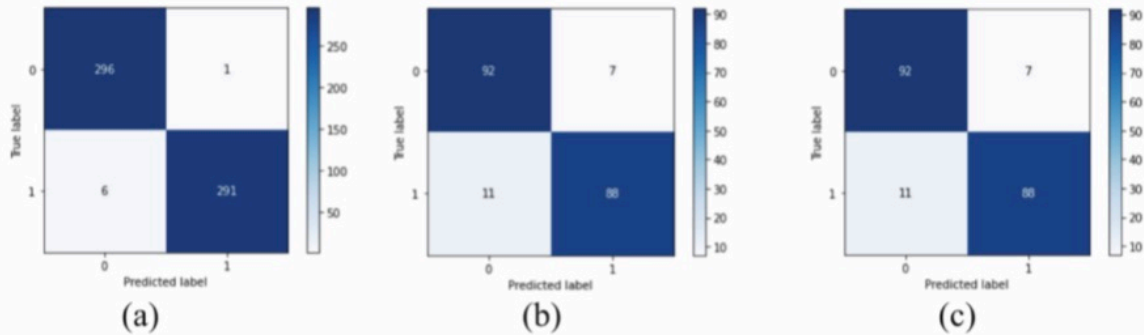


Fig. 4. Confusion matrix for (a) Training (b) Validation (c) Testing of the InceptionV3-RF model.

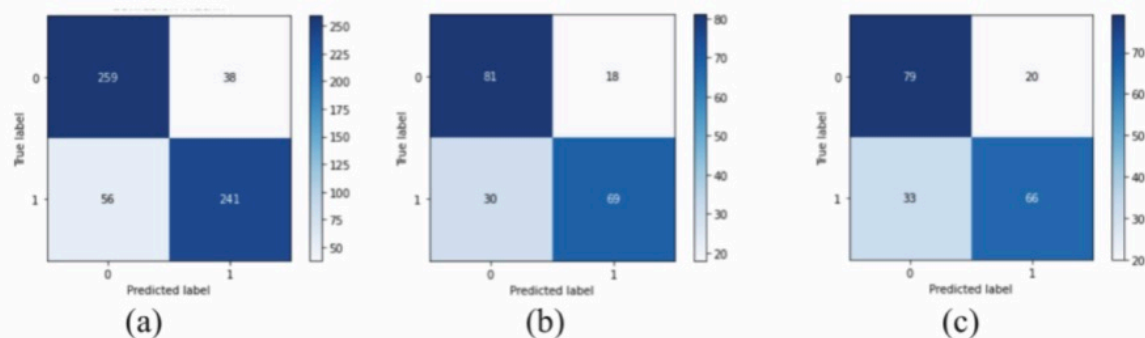


Fig. 5. Confusion matrix for (a) Training (b) Validation (c) Testing of the InceptionV3-kNN model.

4 Conclusion

In this work, the efficacy of a modified transfer learning approach was illustrated in diagnosing oral squamous cell carcinoma. It was shown that the Inception V3 transfer learning model has a desirable quality in yielding reasonably well extraction of the features. This was demonstrated through the classification accuracy yielded by the SVM model that accounted for an average of 91% for the test and validation dataset. Future work shall investigate the efficacy of other transfer learning models along with different classifiers. Moreover, the performance of the present architecture shall further be examined by tuning its hyperparameters.

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