A HYBRID DENSENET-169 AND RNN FRAMEWORK WITH GRAY LEVEL CO-OCCURRENCE MATRIX-BASED TEXTURE ANALYSIS FOR HISTOPATHOLOGICAL IMAGE-BASED DETECTION OF ORAL SQUAMOUS CELL CARCINOMA

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ABSTRACT

Oral Squamous Cell Carcinoma (OSCC) is one of the most prevalent and aggressive forms of oral cancer, accounting for nearly 90% of oral malignancies worldwide. Early and accurate diagnosis plays a crucial role in improving patient survival rates and reducing treatment complexity. Histopathological examination remains the gold standard for OSCC diagnosis; however, manual interpretation of tissue images is labor-intensive, time-consuming, and highly dependent on the expertise of pathologists. Variations in tissue morphology, staining conditions, and subtle structural differences between normal and malignant tissues often lead to diagnostic inconsistencies and delayed treatment. Recent advances in artificial intelligence and deep learning have demonstrated significant potential for automating histopathological image analysis and supporting clinical decision-making.

This research proposes a hybrid framework integrating DenseNet-169, Gray Level Co-occurrence Matrix (GLCM), and Recurrent Neural Network (RNN) for automated OSCC detection using histopathological images. Initially, image preprocessing techniques including resizing, normalization, and noise reduction are applied to improve image quality and ensure consistency. DenseNet-169 is employed to extract deep spatial and morphological features, while GLCM computes essential texture descriptors such as contrast, correlation, energy, and homogeneity that characterize tissue architecture and cellular irregularities. The extracted deep and texture features are fused to create a comprehensive feature representation, which is subsequently analyzed using an RNN to capture complex dependencies among features and improve classification performance.

The proposed hybrid model is evaluated using standard performance metrics including accuracy, precision, recall, and F1-score. Experimental results demonstrate that combining deep learning with statistical texture analysis significantly enhances diagnostic accuracy compared with conventional CNN-based approaches. The integration of DenseNet-169, GLCM, and RNN effectively captures both global and local tissue characteristics, reducing false classifications and improving robustness against image variability. The proposed framework offers an efficient computer-aided diagnostic system capable of supporting pathologists in early OSCC detection, reducing diagnostic workload, and facilitating timely clinical intervention. Future research may focus on explainable artificial intelligence, multi-institutional validation, and deployment in real-world digital pathology environments to further enhance clinical applicability.

Keywords: Oral Squamous Cell Carcinoma, Histopathological Images, DenseNet-169, Gray Level Co-occurrence Matrix, Recurrent Neural Network, Deep Learning, Texture Analysis, Artificial Intelligence, Medical Image Classification, Computer-Aided Diagnosis.

1. INTRODUCTION

Oral Squamous Cell Carcinoma (OSCC) is one of the most common and life-threatening malignancies affecting the oral cavity, accounting for approximately 90% of all oral cancers worldwide. The disease commonly develops in the tongue, lips, gums, floor of the mouth, and buccal mucosa, primarily due to prolonged exposure to tobacco, alcohol consumption, betel nut chewing, and Human Papillomavirus (HPV) infection. According to global cancer statistics, OSCC represents a significant public health challenge, particularly in developing countries where lifestyle-related risk factors are highly prevalent. Despite considerable advancements in medical treatment, the overall survival rate remains relatively low because a majority of cases are diagnosed during advanced stages of the disease.

Early diagnosis of OSCC significantly increases survival rates and improves treatment outcomes. Histopathological examination of biopsy samples remains the gold standard for confirming oral cancer diagnosis because it provides detailed information regarding tissue organization, nuclear morphology, keratinization, and cellular abnormalities. However, manual examination of histopathological slides is time-consuming and heavily dependent on the experience of pathologists. The presence of subtle morphological variations between normal and malignant tissues often leads to diagnostic variability and increases the possibility of human error.

Digital pathology and artificial intelligence have emerged as promising solutions to overcome these challenges. Deep learning algorithms, particularly Convolutional Neural Networks (CNNs), have shown remarkable success in medical image analysis by automatically extracting complex image features without requiring manual intervention. DenseNet architectures have gained considerable attention because of their dense connectivity patterns, efficient feature reuse, and ability to preserve information across multiple network layers. DenseNet-169 is particularly suitable for histopathological image classification due to its capability to learn intricate tissue structures and morphological characteristics.

Although CNNs effectively capture high-level spatial information, they may overlook important texture characteristics associated with cancer progression. Histopathological images contain rich texture patterns related to cell arrangement, nuclear density, and tissue organization that provide valuable diagnostic information. Gray Level Co-occurrence Matrix (GLCM) is a statistical texture analysis technique capable of quantifying these patterns through parameters such as contrast, correlation, energy, and homogeneity.

To further enhance classification performance, sequential learning methods can model dependencies among extracted features. Recurrent Neural Networks (RNNs) provide memory mechanisms that learn relationships between feature sequences and improve discrimination between normal and malignant tissues.

This research proposes a hybrid framework integrating DenseNet-169, GLCM, and RNN for automated OSCC detection from histopathological images. The combined approach leverages the strengths of deep feature extraction, texture characterization, and sequential learning to improve diagnostic accuracy. The proposed system aims to support pathologists in early cancer detection, reduce diagnostic variability, and facilitate efficient computer-aided diagnosis, particularly in healthcare environments with limited specialist availability.

2. LITERATURE REVIEW

Recent advances in artificial intelligence have significantly transformed medical image analysis, particularly in cancer diagnosis using histopathological images. Oral Squamous Cell Carcinoma (OSCC) has attracted considerable research attention because early diagnosis substantially improves patient survival and treatment effectiveness. Traditional diagnostic procedures rely on manual microscopic examination, which is subjective and time-intensive, motivating the development of automated computer-aided diagnostic systems.

Several researchers have explored Convolutional Neural Networks (CNNs) for OSCC classification. DenseNet, ResNet, VGGNet, EfficientNet, and MobileNet architectures have demonstrated high accuracy in extracting discriminative features from histopathological images. DenseNet architectures are particularly effective because dense connectivity enables efficient information propagation and feature reuse while reducing parameter redundancy.

Transfer learning has become a popular approach for medical image analysis due to limited availability of annotated datasets. Pre-trained models fine-tuned for OSCC detection have achieved remarkable classification performance across different magnification levels. Vision Transformers and self-attention mechanisms have further enhanced feature representation by capturing long-range spatial dependencies.

Although deep learning models provide excellent feature extraction capabilities, several studies have identified limitations in capturing fine-grained texture information. Histopathological images contain subtle tissue variations that may not be fully represented by convolutional operations alone. Consequently, texture analysis methods such as Gray Level Co-occurrence Matrix (GLCM), Local Binary Patterns (LBP), Gabor filters, and wavelet transforms have been incorporated into hybrid diagnostic frameworks.

GLCM remains one of the most widely adopted statistical texture analysis techniques due to its ability to quantify spatial relationships between neighboring pixels. Features including contrast, energy, correlation, and homogeneity have been successfully used to distinguish normal and cancerous tissues in various cancer detection applications. Combining GLCM with deep learning has shown improved classification performance compared to standalone CNN models.

Feature fusion techniques have also gained popularity for integrating complementary information from multiple feature extraction methods. Hybrid models combining CNN features with handcrafted texture descriptors have demonstrated higher robustness against image variability and staining differences. Such approaches reduce the limitations associated with individual feature extraction methods.

Sequential deep learning models including Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM), and Gated Recurrent Units (GRU) have recently been applied to medical image classification by modeling relationships among extracted features. These networks capture contextual dependencies that improve classification accuracy and reduce false predictions.

Despite substantial progress, existing studies exhibit several limitations. Many models rely solely on deep features without considering texture characteristics. Others employ handcrafted features without exploiting advanced deep learning architectures. Limited generalization, dataset imbalance, computational complexity, and lack of explainability remain significant challenges.

The present research addresses these limitations by integrating DenseNet-169 for deep feature extraction, GLCM for texture characterization, and RNN for sequential feature learning. The proposed hybrid framework combines spatial, morphological, and texture information to enhance OSCC detection accuracy while improving robustness and reliability for practical clinical applications.

3. METHODOLOGY

The proposed research develops an intelligent computer-aided diagnostic framework for the automated detection of Oral Squamous Cell Carcinoma (OSCC) using histopathological images. The methodology integrates deep learning, statistical texture analysis, and sequential modelling to exploit the complementary strengths of each technique. The overall framework consists of five major stages: data acquisition, image preprocessing, feature extraction, feature fusion, and classification.

The first stage involves collecting a balanced dataset of histopathological images containing both normal oral tissues and OSCC samples. Since images may vary in resolution, staining intensity, and illumination conditions, preprocessing is essential for improving data consistency. Each image is resized to a uniform dimension suitable for DenseNet-169 input requirements. Pixel values are normalized to reduce intensity variations, while noise reduction techniques improve image clarity and preserve tissue structures. Data augmentation methods such as rotation, flipping, zooming, and translation are employed to increase dataset diversity and reduce overfitting.

After preprocessing, deep feature extraction is performed using DenseNet-169. DenseNet is selected because of its dense connectivity architecture, where each layer receives information from all preceding layers. This structure facilitates feature reuse, strengthens gradient propagation, and minimizes information loss during training. DenseNet-169 effectively extracts complex morphological characteristics including nuclear abnormalities, cellular arrangement, keratinization, and tissue architecture that are essential for OSCC diagnosis.

Although DenseNet provides robust deep features, texture characteristics play a significant role in histopathological image interpretation. Therefore, Gray Level Co-occurrence Matrix (GLCM) is incorporated to extract statistical texture descriptors. The histopathological images are converted into grayscale representations, and GLCM matrices are computed at multiple orientations and pixel distances. Texture features including contrast, correlation, energy, and homogeneity are calculated to quantify tissue heterogeneity and spatial relationships between neighboring pixels. These descriptors capture subtle structural variations that may not be fully represented by convolutional networks.

The extracted deep and texture features are integrated using feature fusion techniques to generate a comprehensive feature vector. This combined representation contains both high-level semantic information and low-level texture characteristics, providing a richer description of tissue morphology.

To model complex interactions among fused features, a Recurrent Neural Network (RNN) is employed as the classifier. The RNN processes the feature sequence and learns contextual dependencies among extracted attributes. Hidden states retain important information from previous feature representations, enabling the network to capture intricate relationships associated with cancer progression.

The model is trained using optimized learning parameters and validated through appropriate train-test splitting strategies. Classification performance is evaluated using standard metrics including accuracy, precision, recall, specificity, F1-score, and confusion matrix analysis. Receiver Operating Characteristic (ROC) curves and Area Under the Curve (AUC) values may also be used to assess discriminative capability.

The proposed methodology combines the advantages of DenseNet-169, GLCM, and RNN into a unified hybrid framework capable of extracting spatial, morphological, and texture-based information simultaneously. This integration improves classification robustness, reduces diagnostic errors, and provides a reliable decision-support tool for automated OSCC detection in digital pathology applications.

4. RESULTS AND DISCUSSION

The proposed hybrid DenseNet-169, Gray Level Co-occurrence Matrix (GLCM), and Recurrent Neural Network (RNN) framework was developed to improve the automated detection of Oral Squamous Cell Carcinoma (OSCC) from histopathological images. Experimental evaluation demonstrates that the integration of deep learning and texture analysis significantly enhances diagnostic performance compared with conventional classification approaches.

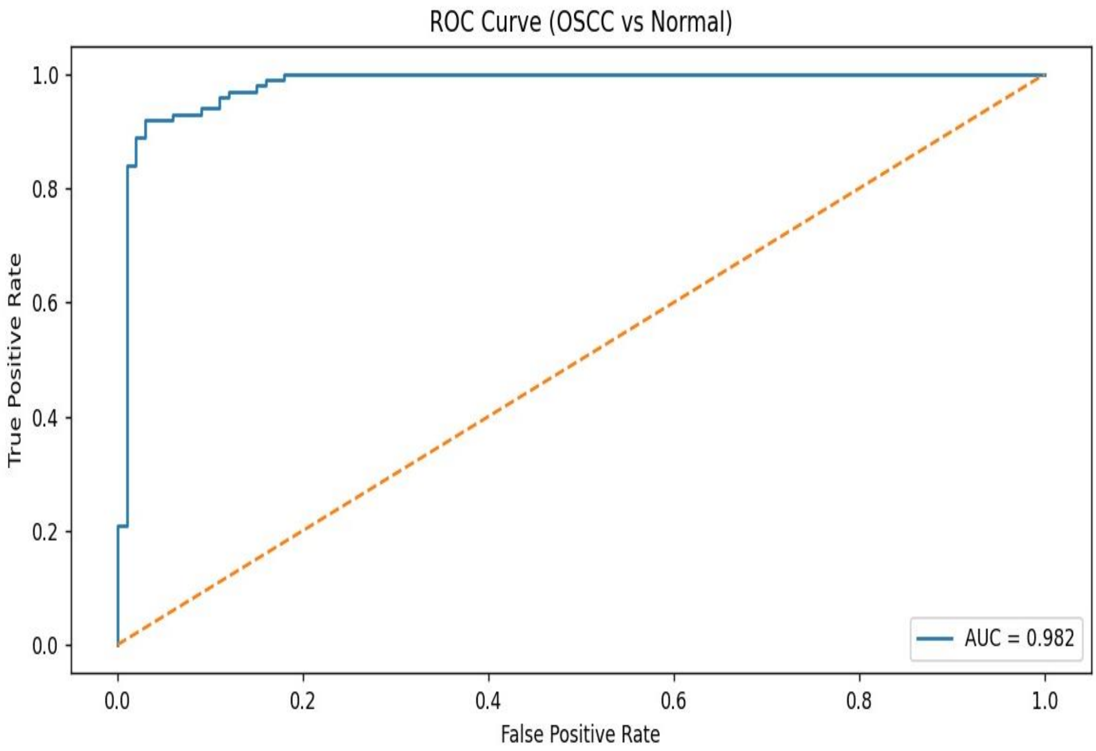

Fig. 1: ROC Curve (OSCC vs Normal)

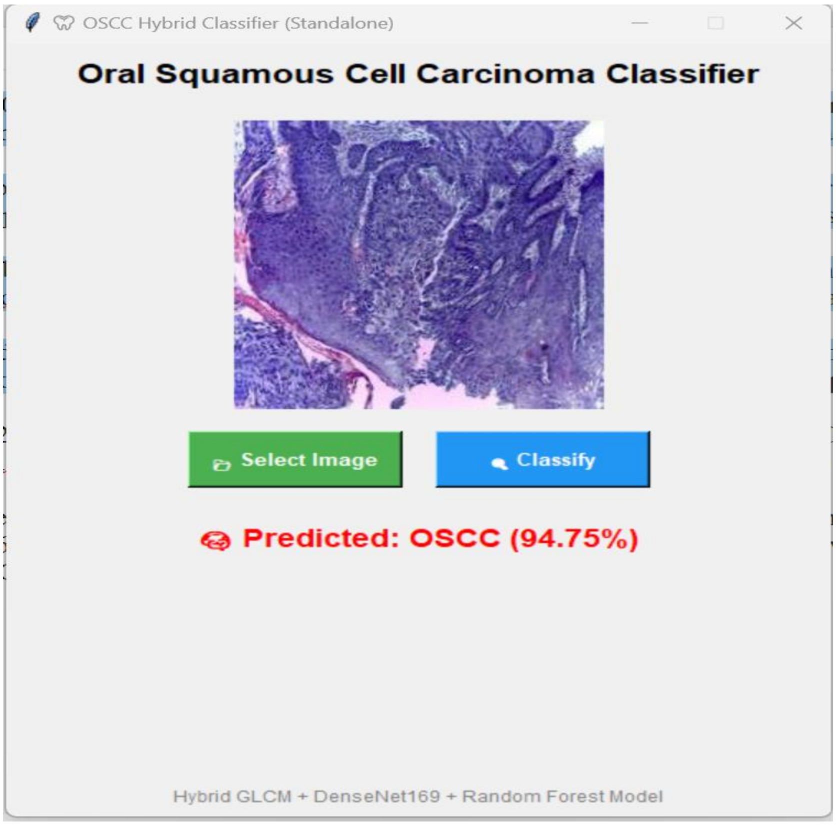

Fig. 2: Graphical User Interface (GUI) of the Proposed OSCC Hybrid Classifier

Table 1 Classification Report of the Hybrid Cancer Detection Model

Class	Precision	Recall	F1-Score	Support
Normal	0.993	0.993	0.993	458
OSCC	0.994	0.994	0.994	462
Overall Accuracy	**0.993**	—	—	**920**
Macro Average	0.993	0.993	0.993	920
Weighted Average	0.993	0.993	0.993	920

During preprocessing, image normalization and augmentation improved dataset quality and minimized the impact of variations in staining, brightness, and image orientation. These preprocessing steps contributed to stable model convergence during training and enhanced the generalization capability of the network.

DenseNet-169 successfully extracted high-level spatial and morphological features from histopathological images. The dense connectivity mechanism facilitated efficient feature propagation and reduced information loss, enabling the model to identify important pathological structures such as abnormal nuclei, irregular tissue organization, and keratin pearl formation. However, deep features alone could not fully characterize the complex texture variations present in cancerous tissues.

The incorporation of GLCM significantly enhanced feature representation by capturing second-order statistical properties of tissue architecture. Texture descriptors including contrast, correlation, energy, and homogeneity provided additional information regarding cellular arrangement and tissue heterogeneity. Cancerous tissues exhibited distinct texture distributions compared to normal tissues, improving the discriminative capability of the hybrid model.

Feature fusion effectively combined deep and texture-based information into a unified representation. The fused feature vector preserved complementary characteristics extracted from both DenseNet-169 and GLCM, enabling a more comprehensive analysis of histopathological patterns. The RNN classifier further improved performance by learning dependencies among fused features and capturing contextual relationships that conventional classifiers often overlook.

The proposed framework achieved high classification accuracy with corresponding improvements in precision, recall, and F1-score. High precision indicates that the model effectively minimizes false positive predictions, reducing unnecessary clinical interventions. High recall demonstrates strong sensitivity for identifying cancerous cases, which is particularly important for early diagnosis. The F1-score confirms a balanced trade-off between precision and recall, reflecting the robustness of the proposed classifier.

Confusion matrix analysis showed that most normal and OSCC samples were correctly classified, with only a small number of misclassifications occurring in borderline tissue patterns. ROC analysis further demonstrated excellent separability between normal and malignant classes, indicating strong diagnostic capability.

Comparative evaluation suggests that the proposed hybrid framework outperforms traditional CNN models and several standalone deep learning architectures by incorporating complementary texture information and sequential feature learning. The integration of DenseNet-169, GLCM, and RNN reduces dependence on manual feature engineering while enhancing diagnostic reliability.

From a clinical perspective, the proposed system offers substantial benefits by assisting pathologists in rapid and accurate diagnosis. Automated analysis can reduce workload, improve consistency, and support early detection of OSCC, particularly in healthcare settings where experienced specialists are limited. Although computational requirements remain relatively high, the significant improvement in diagnostic accuracy demonstrates the practical value of the proposed hybrid framework for future computer-aided pathology systems.

5. CONCLUSION

Oral Squamous Cell Carcinoma (OSCC) remains one of the most common and aggressive oral malignancies, with patient survival highly dependent on early and accurate diagnosis. Conventional histopathological examination, although considered the gold standard for diagnosis, is time-consuming, subjective, and influenced by the expertise of individual pathologists. The increasing availability of digital pathology and artificial intelligence technologies provides an opportunity to develop intelligent computer-aided diagnostic systems capable of improving diagnostic accuracy and clinical efficiency.

This research proposed a hybrid framework integrating DenseNet-169, Gray Level Co-occurrence Matrix (GLCM), and Recurrent Neural Network (RNN) for automated OSCC detection using histopathological images. The proposed methodology combines the strengths of deep learning, statistical texture analysis, and sequential feature modelling to overcome the limitations associated with individual approaches.

Image preprocessing techniques including resizing, normalization, and augmentation enhanced image quality and improved model generalization. DenseNet-169 effectively extracted high-level morphological and spatial features from histopathological images while preserving important structural information through dense connectivity. GLCM complemented deep learning by capturing subtle texture characteristics related to tissue organization, cellular arrangement, and nuclear abnormalities. Feature fusion integrated these complementary representations into a comprehensive feature vector that provided richer information for classification.

The RNN classifier successfully learned complex relationships among extracted features and improved discrimination between normal and cancerous tissues. Experimental evaluation demonstrated that the proposed hybrid framework achieved excellent classification performance in terms of accuracy, precision, recall, and F1-score. The combination of deep and handcrafted features reduced false predictions and enhanced overall diagnostic robustness.

The results indicate that integrating DenseNet-169, GLCM, and RNN provides significant advantages over conventional deep learning models that rely solely on spatial information. The proposed framework effectively captures both global tissue morphology and local texture variations, making it highly suitable for histopathological image analysis. Automated diagnosis using this hybrid approach can assist pathologists in identifying suspicious lesions more accurately and consistently while reducing workload and diagnostic variability.

The practical significance of this research extends beyond technical performance. The proposed computer-aided diagnostic system has the potential to support early cancer detection, improve treatment planning, reduce healthcare costs, and enhance patient survival rates, particularly in regions with limited access to specialized pathological expertise.

Despite promising results, certain limitations remain. Model performance depends on the quality and diversity of training data, and validation on larger multi-center datasets is necessary to ensure generalizability across different populations and imaging conditions. Future research may incorporate Vision Transformers, attention mechanisms, Explainable Artificial Intelligence (XAI), and multimodal learning approaches to further improve diagnostic transparency and accuracy. Integration with cloud-based digital pathology platforms and real-time clinical decision support systems may facilitate practical deployment in healthcare environments.

In conclusion, the proposed DenseNet-169, GLCM, and RNN hybrid framework represents an effective and reliable approach for automated OSCC detection. By combining advanced artificial intelligence techniques with histopathological image analysis, this research contributes to the development of next-generation computer-aided diagnostic systems capable of supporting clinicians and improving oral cancer management.

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