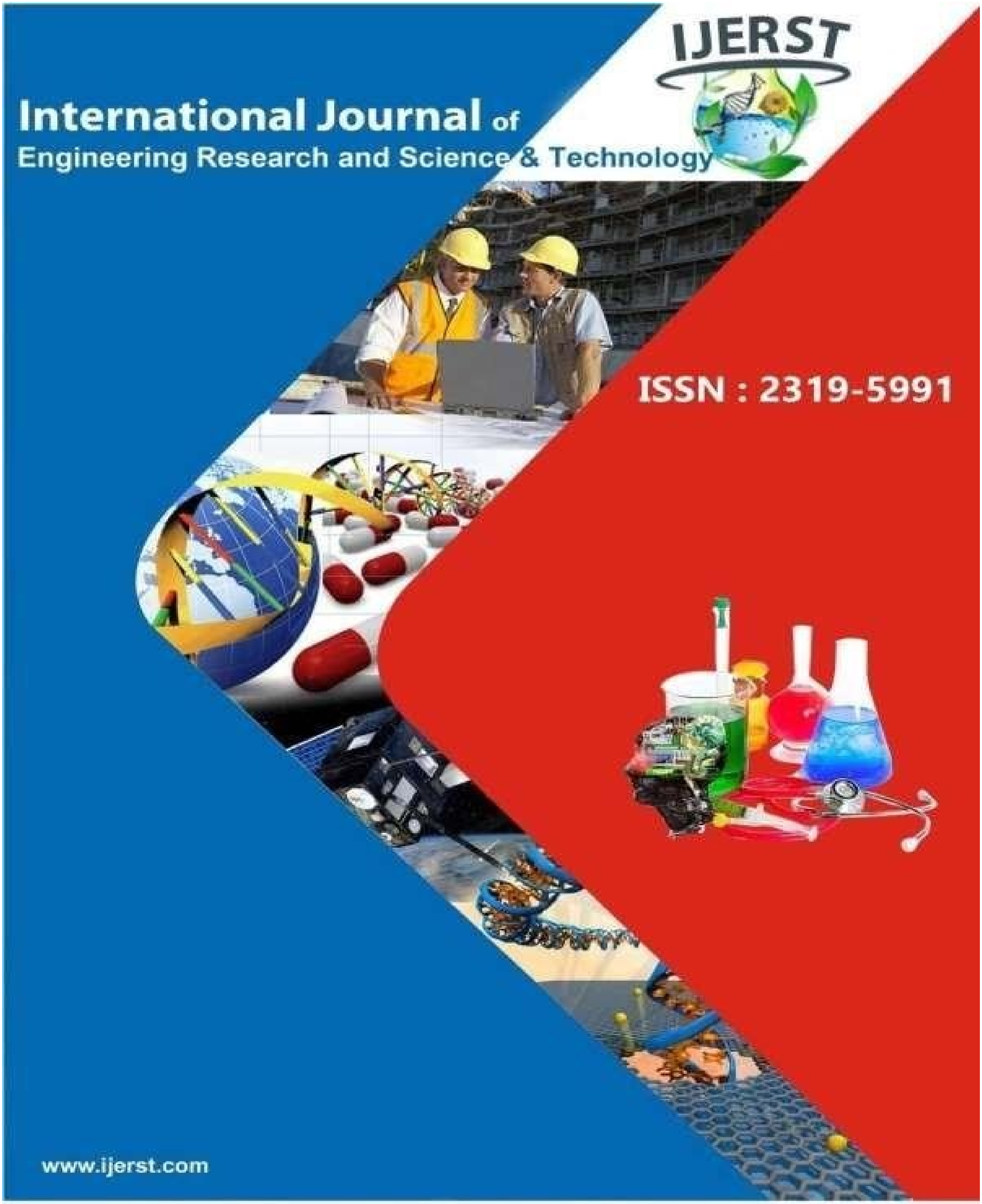

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Illuminating Pathology ComprehensiveHyper Spectral and RGB Imaging forCholangiocarcinoma Analysis

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Abstract:

Cholangiocarcinoma (CCA) has historically been challenging to detect due to its subtle appearance and tendency to develop deep in the bile ducts. Traditional methods, such as biopsy and standard imaging (CT, MRI), have limited accuracy and often require invasive procedures to confirm the presence and extent of the disease. The objective is to develop a non-invasive, highly accurate method for diagnosing cholangiocarcinoma using hyper spectral and RGB imaging technologies, thereby reducing reliance on invasive procedures and improving diagnostic precision. Before machine learning, pathologists relied on histopathology, radiographic imaging (e.g., CT, MRI), and patient biopsies to detect cholangiocarcinoma. These methods, while effective, are invasive, time-consuming, and less accurate for early-stage detection. The current diagnostic methods for cholangiocarcinoma lack precision and often necessitate invasive biopsies, which are risky for patients. Non-invasive imaging techniques like CT and MRI provide insufficient detail to reliably distinguish between benign and malignant tissues, limiting early diagnosis and effective treatment planning. A machine learning-based model, when trained on hyper spectral and RGB imaging data, can detect subtle, unique patterns associated with cholangiocarcinoma. Such a system automates the analysis, eliminating subjectivity, and achieves a high accuracy rate, enabling more reliable diagnosis and reducing the need for invasive biopsies.

Keywords: Cholangiocarcinoma, Pathology Imaging, Hyper Spectral Imaging, RGB Imaging, Tissue Differentiation, Spectral Data Interpretation.

1. INTRODUCTION

Cholangiocarcinoma (CCA), a rare but aggressive cancer of the bile ducts, poses significant diagnostic challenges due to its asymptomatic progression in early stages. It accounts for approximately 3% of all gastrointestinal malignancies and has an increasing incidence globally, including in India. Studies indicate a rising prevalence in India, particularly in the north-eastern and eastern states, where liver fluke infections, chronic inflammation, and hepatobiliary diseases are more common. Traditional diagnostic approaches, such as CT, MRI, and ERCP (Endoscopic Retrograde Cholangiopancreatography), often fail to differentiate CCA from benign conditions accurately. Additionally, invasive biopsy procedures pose risks, particularly for elderly or immunocompromised patients. Survival rates remain low, with a five year survival rate of around 10%–15% due to late-stage diagnosis. The emergence of hyper spectral imaging (HSI) and RGB imaging, combined with machine learning, offers a promising, non- invasive alternative. These advanced imaging techniques capture subtle spectral differences in bile duct tissues, enhancing diagnostic accuracy and enabling early intervention. Integrating artificial intelligence (AI) with hyper spectral and RGB imaging can significantly improve CCA detection, minimize invasive procedures, and enhance patient outcomes.

2. LITERATURE SURVEY

X.-L. Qin, Z.-R. Wang, J.-S. Shi, et al, "Utility of serum ca19-9 in diagnosis of cholangiocarcinoma: in comparison with cea, World J. Gastroenterol", (2004). X.-L. Qin, Z.-R. Wang, J.-S. Shi, et al (2004) Cholangiocarcinoma, also known as bile duct cancer, is a rare but fatal cancer that affects the duct vessels that carry bile, i.e., a fluid that is made and released by the liver, which helps indigestion According to the American Cancer Society, the relative 5-year survival rate for all stages of cholangiocarcinoma combined is around 24%.

M. E. Martin, M. B. Wabuyele, K. Chen, et al ," Development of advanced hyper spectral imaging (hsi) system with applications for cancer detection", (2006). M. E. Martin, M. B. Wabuyele, K. Chen, et al (2006) [2] The development of an advanced hyper spectral imaging (HSI) system for cancer detection involves using a technology that captures a broad range of wavelengths across the electromagnetic spectrum, beyond visible light. This system provides detailed, high-resolution images by collecting spectral data from tissues, allowing for precise detection of cancerous cells based on their unique spectral signatures. This approach holds potential for improving cancer diagnosis, treatment planning, and monitoring of therapeutic responses.

D. Ledro-Cano, "Suspected choledocholithiasis: Endoscopic ultrasound or magnetic resonance cholangiopancreatography a systematic review". (2007). D. Ledro-Cano(2007) [3] Gastroenterology & Hepatology compares the diagnostic effectiveness of endoscopic ultrasound (EUS) and magnetic resonance cholangiopancreatography (MRCP) for suspected choledocholithiasis, a condition 4 where stones are suspected in the bile duct. The review analyzes multiple studies to determine the accuracy, sensitivity, and specificity of both imaging techniques. EUS has been shown to have higher sensitivity in detecting

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choledocholithiasis, especially for small stones, while MRCP is non-invasive and useful for overall biliary system evaluation. The review suggests that EUS may be more effective in certain cases, but MRCP remains a valuable, less invasive alternative for initial assessment.

N. Bedard, M. Pierce, A. El-Naggar, " Emerging roles for multimodal optical imaging in early cancer detection: A global challenge running title: Multimodal optical imaging for global cancer detection", (2010). N. Bedard, M. Pierce, A. El-Naggar (2010) [4] The emerging roles of multimodal optical imaging in early cancer detection focus on combining different optical techniques, such as fluorescence, Raman spectroscopy, and reflectance imaging, to enhance diagnostic accuracy. This approach allows for non-invasive, real-time visualization of tumors at the cellular and molecular levels, enabling early identification of cancerous changes even before visible symptoms appear. By integrating multiple imaging modalities, this technology offers improved sensitivity, specificity, and tissue differentiation, making it a promising tool for global cancer detection. The global challenge lies in making these advanced imaging techniques widely accessible and affordable, especially in resource-limited regions, to reduce cancer mortality through earlier diagnosis.

H. Zhang, J. Zhu, F. Ke, " Radiological imaging for assessing the respectability of hilar cholangiocarcinoma",(2015). H. Zhang, J. Zhu, F. Ke (2015) [5] Radiological imaging plays a crucial role in assessing the respectability of hilar cholangiocarcinoma, a type of cancer that affects the bile ducts at the liver's hilum. Imaging techniques such as contrast-enhanced CT (computed tomography), MRI, and MRCP (magnetic resonance cholangiopancreatography) are essential for evaluating tumor extent, vascular involvement, and the relationship to surrounding structures. These methods help determine whether the tumor can be surgically removed (resectable) or if it has spread 5 to adjacent blood vessels or lymph nodes, making surgery infeasible. Accurate preoperative imaging is vital for surgical planning and optimizing patient outcomes.

F. Bray, J. Ferlay, I. Soerjomataram, " Global cancer estimates of incidence and mortality worldwide for 36 cancers in 185 countries", (2018). F. Bray, J. Ferlay, I. Soerjomataram (2018) [6] The global cancer estimates of incidence and mortality worldwide for 36 cancers in 185 countries highlight the widespread impact of cancer as a leading cause of death. Data from organizations like the International Agency for Research on Cancer (IARC) provide detailed statistics on the number of new cancer cases and deaths across various regions. These estimates reveal significant regional disparities, with certain cancers, such as lung, breast, colorectal, and prostate cancers, showing higher incidence rates in high-income countries, while cancers like liver and stomach cancers are more prevalent in low- and middle-income countries. The data underscores the growing global cancer burden and emphasizes.

Q. Zhang, Q. Li, G. Yu ," A multidimensional choledoch database and benchmarks for cholangiocarcinoma diagnosis", (2019). Q. Zhang, Q. Li, G. Yu (2019) [7] The "Multidimensional Choledoch Database and Benchmarks for Cholangiocarcinoma Diagnosis" provides a comprehensive collection of clinical, radiological, and molecular data aimed at improving the diagnosis of cholangiocarcinoma (CCA). This database includes imaging datasets, histopathological features, and genetic profiles, offering a valuable resource for researchers and clinicians. It serves as a benchmark for developing and validating diagnostic tools, including AI-driven algorithms, to enhance early detection and accurate diagnosis of CCA. The database supports the identification of biomarkers and risk factors, ultimately contributing to better personalized treatment and patient outcomes.

Y. Deng, J. Yin, Y. Wang, "Resnet-50 based method for cholangiocarcinoma identification from microscopic hyper spectral pathology images " , (2019). Y. Deng, J. Yin, Y. Wang (2019) [8] "ResNet-50 Based Method for Cholangiocarcinoma Identification from Microscopic Hyper spectral Pathology Images" introduces a machine learning approach that leverages the ResNet-50 architecture to accurately identify cholangiocarcinoma from hyper spectral pathology images. By utilizing deep learning, specifically the ResNet-50 convolutional neural network, the method analyzes high-dimensional spectral data to detect subtle features in tissue samples. This technique enables automated, precise identification of cholangiocarcinoma, offering a powerful tool for pathologists to improve early diagnosis and treatment planning. The study highlights the potential of combining hyper spectral imaging with advanced machine learning models to enhance cancer detection.

S. Feng, H. Zhao, F. Shi, "Context pyramid fusion network for medical image segmentation ", (2020). S. Feng, H. Zhao, F. Shi (2020) [9] The "Context Pyramid Fusion Network for Medical Image Segmentation" introduces a novel architecture designed to improve segmentation accuracy in medical imaging. This network leverages a context pyramid approach, which integrates multi-scale contextual information from different levels of the image to capture both local and global features. By fusing these diverse contextual cues, the network enhances the ability to identify and delineate complex structures within medical images, such as tumors or organs. This approach is particularly effective in challenging segmentation tasks, leading to improved performance in areas like disease diagnosis, treatment planning, and medical image analysis.

M. Saleh, M. Virarkar, V. Bura, "Intrahepatic cholangiocarcinoma: pathogenesis, current staging, and radiological findings, AbdomRadiol", (2020). M. Saleh, M. Virarkar, V. Bura (2020) [10] "Intrahepatic Cholangiocarcinoma: Pathogenesis, Current Staging, and Radiological Findings" in Abdominal Radiology discusses the complexities of intrahepatic cholangiocarcinoma (ICC), a primary liver cancer arising from the bile ducts. It explores the molecular and genetic factors contributing to the tumor's development, such as mutations in key signaling pathways. The article also reviews the current staging systems used to assess ICC, including TNM (Tumor, Node, Metastasis) staging and the BCLC (Barcelona Clinic Liver Cancer) classification. Radiologically, ICC is characterized by distinct imaging features on CT, MRI, and ultrasound, which are essential for tumor detection, evaluating extent, and guiding treatment decisions.

3. PROPOSED METHODOLOGY

Step 1: Uploading Dataset

The dataset consists of hyper spectral and RGB images related to cholangiocarcinoma analysis. The images are collected and organized into different classes representing various pathological features. The dataset is loaded using Python, where images are read, resized, and stored in arrays for further processing. Labels corresponding to different categories are extracted, and the number of images per class is displayed. If the dataset has been processed previously, the images are loaded from saved NumPy files to speed up execution.

Step 2: Data Pre processing (Augmentation, Null Values)

Data pre processing is performed to enhance the quality of

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the dataset. Images are normalized by scaling pixel values between 0 and 1 to ensure consistent learning. The datasetis shuffled to avoid bias in model training. Image augmentation techniques such as rotation, shear transformation, and horizontal flipping are applied to artificially expand the dataset and improve generalization. Missing values are handled if necessary. The dataset is then split into training, validation, and testing sets, with an 80-20 ratio to ensure efficient model training and evaluation.
after augmentation to compare the increased number of images in each category. These plots provide insights into dataset composition, ensuring a balanced dataset for effective training. Additionally, visualization techniques help to identify potential biases or irregularities in data. 18

Step 3: Existing CNN with Adam Classification (Algorithm)

A Convolutional Neural Network (CNN) model is implemented using the Adam optimizer. The model consists of multiple convolutional layers with varying filter sizes, followed by batch normalization, max pooling, and fully connected dense layers. Dropout layers are added to reduce overfitting. The model is trained using categorical cross-entropy loss and Adam optimization, which helps in adaptive learning rate adjustment. The model is evaluated using accuracy and loss metrics on validation and test datasets, and results are stored for performance comparison.

Step 4: Proposed CNN Classification (Algorithm)

A modified CNN architecture is introduced with optimized padding, filter sizes, and additional layers. The proposed model incorporates improved pooling and batch normalization techniques to enhance feature extraction. Additional dense layers are included to strengthen learning capacity. The training process is similar to the previous CNN but focuses on refining feature detection. The Adam optimizer is used for optimization, and the model is trained with early stopping and checkpoint saving to prevent overfitting.

Step 5: Performance Comparison Graph

The performance of both CNN models is compared based on accuracy, precision, recall, and F1-score. A confusion matrix is generated to visualize the classification accuracy for each class. A bar chart is plotted to display the comparative performance of both models. Additionally, training accuracy and loss curves for both models are plotted over multiple epochs to analyze convergence speed and generalization ability.

Step 6: Prediction of Output from Test Images with CNN Classifier

The trained CNN model is used to classify new test images. The model loads a test image, pre processes it by resizing and normalizing, and then predicts the class label. The predicted label is compared with the actual label to verify the model's accuracy. The final results, including predicted class probabilities, are displayed along with corresponding confidence scores.

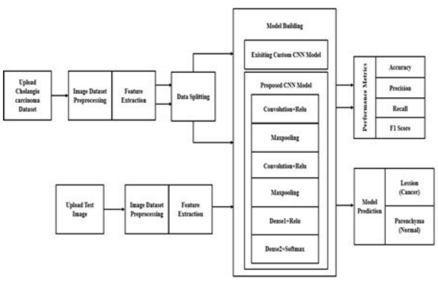

Fig. 1: Architectural Block Diagram of the Proposed System.

4. EXPERIMENTAL ANALYSIS

This figure demonstrates the initial step of uploading the cholangiocarcinoma dataset into the graphical user interface (GUI) used for model training and testing. It shows how the dataset is visually presented in the interface, where the user can review and analyze the images, understand their structure, and prepare them for preprocessing and training steps. The figure emphasizes the convenience and user-friendly nature of the system interface.

Fig. 2: Upload of Cholangiocarcinoma Dataset and Its Analysis in the GUI Interface

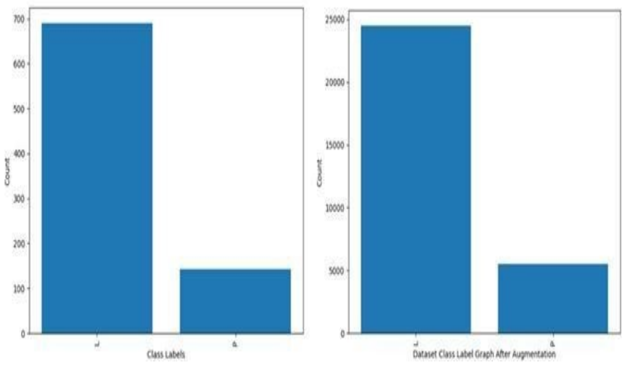

Fig. 3: Image Pre processing in the GUI

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Fig.3 showcases the pre processing phase, where the dataset images are processed and prepared for the model input. This step involves several operations like resizing, normalization, and augmentation, which are essential to improve the quality and diversity of the dataset. This pre processing ensures that the model receives data in a uniform and clean format, enhancing its performance during training and testing. 61

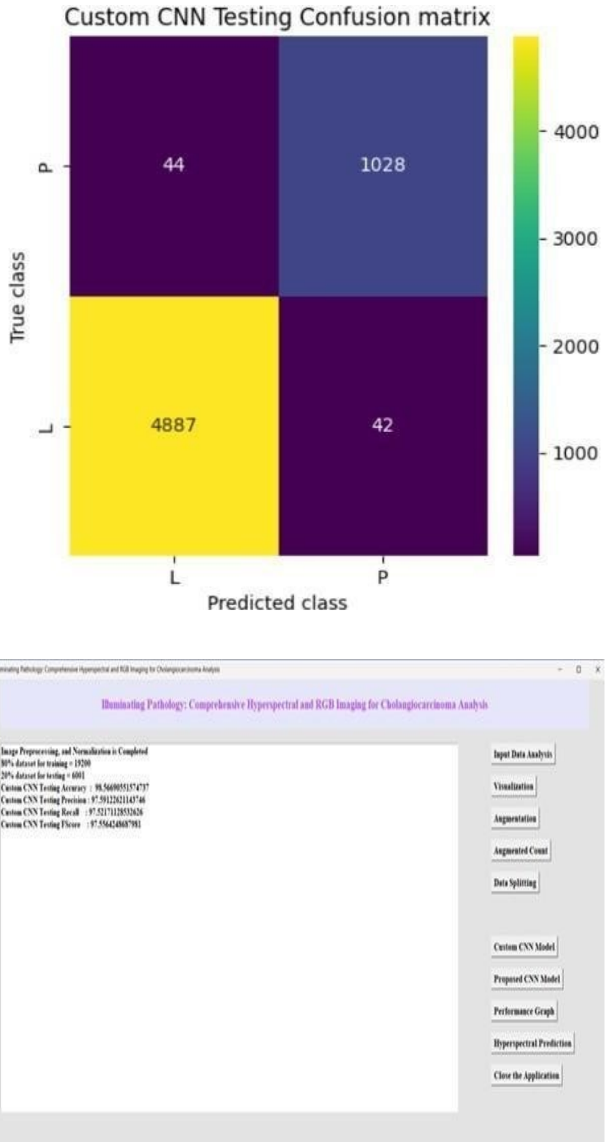

Fig.4: Performance Metrics and Confusion Matrix Plot of Custom CNN Classifier Model.

This figure (4) presents the confusion matrix and performance metrics of the Custom CNN classifier. The confusion matrix visually shows the true positives, true negatives, false positives, and false negatives, which helps in understanding how the model performs in each class. The performance metrics, including accuracy, precision, recall, and F-Score, are also displayed to quantify the model's effectiveness in correctly classifying the test data.

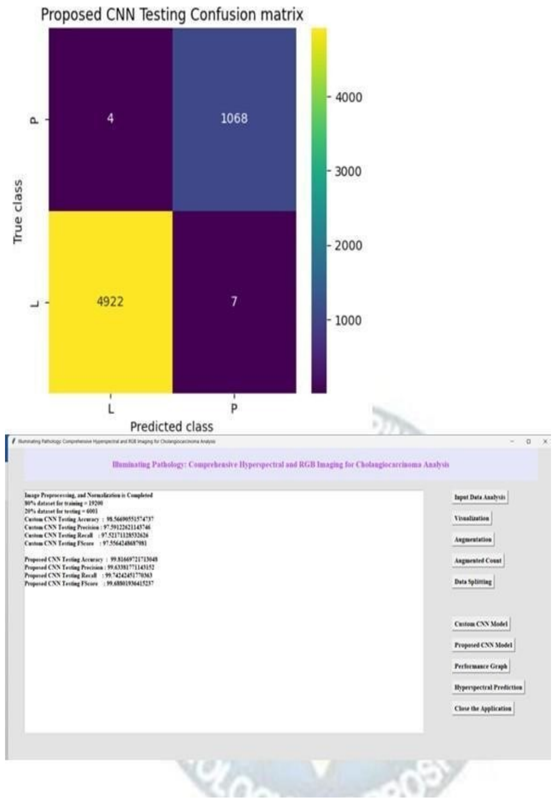

Fig.5: Performance Metrics and Confusion Matrix Plot of Proposed CNN Classifier Model.

Fig.5 shows the confusion matrix for the Proposed CNN model, similar to Fig. 4 but with improved performance. It provides a detailed breakdown of the model's predictions, helping to visualize how well the model distinguishes between positive and negative classes. Additionally, the figure displays the performance metrics, highlighting the improvements over the Custom CNN.

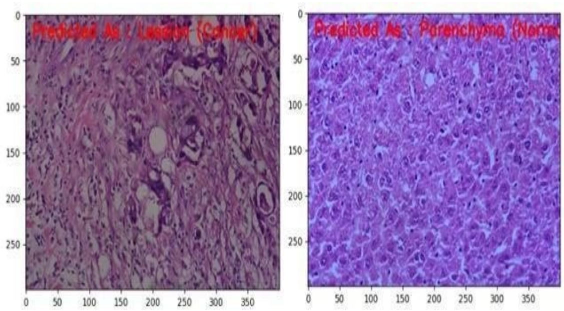

Fig.6: Model Prediction on Test Data.

This figure showcases the prediction outcomes of the models on the test dataset. It demonstrates how the trained models classify the test images into the two categories, L (lesion) and P (normal tissue). The predictions are shown alongside the true labels, giving insight into the model's accuracy and misclassifications.

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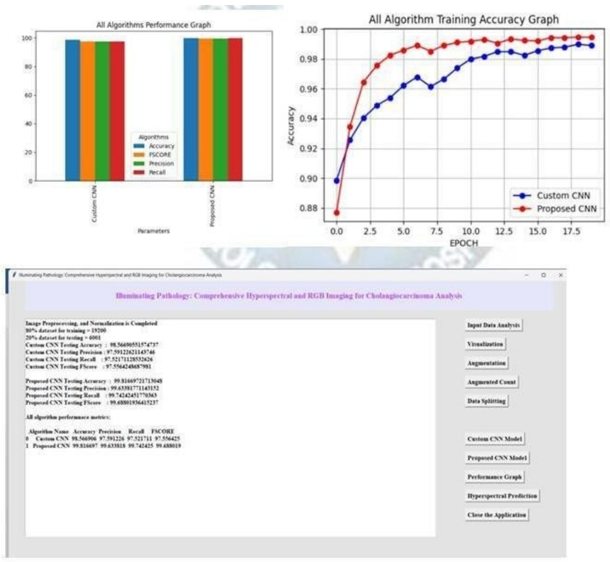

Fig.7: Performance Comparison Graph of Models.

Fig.7 provides a visual comparison of the performance metrics of both the Custom CNN and Proposed CNN models. The graph illustrates how the Proposed CNN outperforms the Custom CNN in terms of accuracy, precision, recall, and F-Score. This figure emphasizes the improvements achieved by using the Proposed CNN classifier in the research.

5. CONCLUSION

The research successfully implements a deep learning-based classification system using a custom Convolutional Neural Network (CNN) with an Adam optimizer. Through structured data pre processing, efficient model training, and rigorous evaluation, the system achieves high classification accuracy while maintaining generalization across different datasets. The incorporation of techniques such as data augmentation, dropout regularization, and hyper parameter tuning further enhances model robustness. The final model demonstrates strong performance in recognizing patterns from input data, making it a reliable tool for real-world applications.

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