Performance Analysis Based on Deep Learning Architecture to Track Out Cholangiocarcinoma

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Abstract. Deep learning has recently garnered significant attention for developing fast, automated, and accurate image classification and identification systems. This study focuses on enhancing and evaluating state-of-the-art deep convolutional neural network (CNN) architectures for imaging-based cholangiocarcinoma classification. The architectures analyzed include ResNet152V2, MobileNetV2, InceptionV3, Xception, VGG19, and DenseNet201. The experimental dataset comprised medical images of healthy and affected common bile duct tissue from 174 individuals, categorized into three groups. The primary objective was to establish a reliable and efficient model for early cholangiocarcinoma diagnosis using precise and rapid analytical methods. DenseNet201 demonstrated superior performance, exhibiting no signs of overfitting and achieving a test accuracy of 93%, outperforming other architectures in original and transfer learning approaches. Furthermore, DenseNet201 achieved this high performance with fewer parameters and reduced computational cost. The models were trained using the Keras framework with a Theano backend. This research provides valuable insights for data scientists and medical professionals seeking to improve diagnostic accuracy in cholangiocarcinoma detection.

Keywords: Cholangiocarcinoma Detection, Deep Learning, CNN, Transfer Learning, Disease Detection.

1 Introduction

Data scientists have modified their approach to use Convolutional neural networks with deep layers (D-CNN) for cholangiocarcinoma detection, classification, and segmentation due to the visible advantages of D-CNN in medical image analysis [1]. The enormous amounts of data generated by scan centers necessitate a significant amount of

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time and effort spent on the part of doctors and radiologists for the classification process, D-CNN illustrates exceptional performance when resolving issues with classification based on difficult tasks such as fractionalization of cholangiocarcinoma cells in medical image scans [2] [3].

When the initial tumor expands to the stage where a significant liver mass is formed or when hepatitis develops as a result of biliary branch obstructions, CCA is frequently identified at a more advanced stage. In particular, 60– 70% of CCA patients were identified to have distant tumors or local invasion, which considered aggressive treatment unfeasible. Less than a year was the median total survival time [2][4][6]. It is generally recognized that cholestasis and ongoing inflammation cause anomalies in several intracellular pathways that are regulated by multiple proto-oncogenes, which in turns causes cholangiocarcinoma [5]. The identification and treatment of diseases mainly depend on histopathology investigation. As artificial intelligence evolved, an increasing number of pathological databases for histopathological detection have been reported. Microscopy hyperspectral images of a patient's liver among digital images are an effective tool for identifying cholangiocarcinoma. Large data sets and various kinds of cholangiocarcinoma as make the traditional method costly and susceptible to human error [4].

1.1 Motivation

Cholangiocarcinoma usually requires two approaches: detection and segmentation. These have recently been made accessible. Unfortunately, these approaches are labor-intensive and susceptible to inaccuracy since they require manual tumor segmentation and feature extraction. It requires an automated tumor diagnostic technique to precisely extract features and detect cholangiocarcinoma [7]. The use of D-CNN for cholangiocarcinoma detection is one approach. Since the approach is less susceptible to mistakes and is time-consuming, it is dependent upon the detection and classification of cholangiocarcinoma based on medical photographs [6] [8]. The primary target of this research is to use MRI images and a D-CNN to detect, segment, and categorize cholangiocarcinoma. This research will use the D-CNN with transfer learning, region-based convolution neural networks (R-CNN), and the traditional CNN architecture. This study investigated the original CNNs Resnet152V2, InceptionV3, Xception, MobileNetV2, DenseNet201, and VGG19. Several types of width-based, depth-based, and spatial-based architecture are included in the array of original CNN [9]. The study that examined deep CNN is needed for image processing has an impact on the objective as well. whereas CNN-based architectures have been developed and used in this study to address the problem of cholangiocarcinoma classification, including VGG19, Resnet152V2, InceptionV3, Xception, MobileNetV2, and DenseNet201.

Despite the breakthrough in cholangiocarcinoma research applying D-CNN, current academics of the case study claim that despite substantial advances in the creation of CAD in identifying cholangiocarcinoma, the approaches face obstacles owing to poor accuracy. The erroneous categorization of the liver will lead to disastrous effects. Consequently, understanding the proper kind Thus the early tumor grade plays an essential part to play in establishing a specific treatment strategy [4]. However, most existing research approach cholangiocarcinoma for detection, whereas the type of the tumor,

stage of the tumor, and related information on the tumor remain under- researched. Our observation is also supported by the study of, who purported that more research works toward cholangiocarcinoma classification should be implemented.

1.2 Expected Outcome

The main significance of this study is that the cholangiocarcinoma patient is expected to benefit from a more accurate diagnosis of tumors than before, providing an opportunity for proper treatment. An effective treatment plan and an accurate diagnosis of cholangiocarcinoma depend on early detection. We investigate a novel CNN approach based on deep learning that offers good accuracy in the diagnosis and classification of cholangiocarcinoma by processing RGB pictures. This is because despite a handful of research devoted in cholangiocarcinoma research, recently criticizes the substantial false-positive results and poor accuracy in cholangiocarcinoma studies. More features will contribute toward the accuracy of the detection/classification process of cholangiocarcinoma which will accelerate the development of the cholangiocarcinoma research area.

2 Literature review

The tumour's location significantly influences the available surgical procedures, treatment decisions for advanced stages, and the overall prognosis [1]. Between 50% and 60% of cases belong to the perihilar cholangiocarcinoma (pcca) subtype, with distal cholangiocarcinoma (dcca) accounting for approximately 25% of instances, and intrahepatic cholangiocarcinoma (icca) representing about 20% of cases. Despite variations in histologic subtypes, most cases are identified as sclerosing-type carcinomas. Forner, A., Vidili, G. (2019), and colleagues addressed Cholangiocarcinoma (CCA) in their study, focusing on clinical presentations, diagnostic methodologies, and staging techniques. They highlighted the importance of understanding CCA's clinical manifestations, employing effective diagnostic strategies including imaging, and accurately staging the disease, as these phases significantly influence the formulation of a successful treatment strategy [2].

Zhang, Q., Li, Q., Yu, G., et al. (2019) conducted a study that categorised a multidimensional choledoch database containing hyperspectral microscopy and RGB colour images with meticulous labelling [3]. The study aimed to achieve the following objectives: a) to provide a comprehensive and up-to-date review of pathological imaging systems; b) Offer a detailed describing of the proposed database, including the login method; and c) to announce that the multidimensional database has been released and is available for download after registration, with access information provided on the official website.

Most intrahepatic cholangiocarcinomas typically present as a single mass, predominantly located in the right lobe of the liver (approximately 35%), compared to the left lobe (about 22%) [4][5]. A smaller proportion of these tumours are centrally located (around 12%), while others may appear as multiple growths (approximately 31%).

These algorithms play a crucial role in automating and enhancing the accuracy of image analysis, aiding in the early detection and precise diagnosis of cholangiocarcinoma [6]. Duangkumpha, K., Stoll, T. (2019) et al. carried out serum protein biomarker discovery [7]. The process involved shotgun without labels, where 30 participants (n = 10 for the "USnormal, US-PDF, and CCA groups") had depleting serum samples on which proteomics was conducted. Using supervised multivariate statistical analysis, 11 discriminating proteins were found among the 40 protein candidates selected (n = 30 per group) based on repeated reaction monitoring on an additional 90 samples. This process of discovery and qualification is crucial as it identifies potential biomarkers that can aid in the early detection and accurate diagnosis of cholangiocarcinoma. Using ELISA and immunohistochemistry (IHC), we further assessed 3 candidates. Infiltrating tumour stroma immune cells included S100A9, which was found. Depleted sera exhibited encouraging results from proteomics discovery and qualification [8].
Ultrasound was used to confirm the presence of a PDF or a normal bile duct in 42 patients' pooled urine samples used for the biomarker development process [9]. After high-abundance proteins were removed, 338 urine proteins remained. Seventy potential proteins were chosen based on fold change and thorough research for further evaluation using MRM-MS. These proteins were tested across 90 urine samples, with 30 samples in each group [10].

Sciarra, A., Park, Y. N. (2020) et al. investigated the important points of the 2018 agreement, which is now included in the 2019 WHO classification, and provide a brief survival guide to assist surgical pathologists encountering cHCC-CCA in their usual workup [8]. Gad et al. classified the SEER 18 database analyzed cholangiocarcinoma cases in the United States spanning from 2000 to 2015. This investigation delved into the incidence and death rates of cholangiocarcinoma among different racial groups, expressed per 1,000,000 person-years. Researchers employed join-point regression software to calculate the Annual Percent Change (APC). The study encompassed 16,189 cholangiocarcinoma patients, with the majority (64.4%) presenting with intrahepatic tumors. The demographic profile showed a predominance of white individuals (78.4%), men (51.3%), and individuals aged over 65 years (63%). These were notably higher among Asians, men, and those aged over 65. The study observed a significant increase in incidence rates over the study duration. Similarly, mortality rates also exhibited a significant rise in study time, although there was a subsequent decrease after 2013 (APC $= -25.029$, $P < .001$).

Lapitz et al. serial ultracentrifugation were used to separate serum and urine EVs, which were then examined using transmission electron microscopy, immunoblotting, and nanoparticle tracking analyses [11]. An Illumina gene expression array was utilized to scrutinize the transcriptome of extracellular vesicles (EVs), encompassing both messenger RNAs and non-coding RNAs. The examination revealed 105 and 39 transcripts that exhibited frequent alterations in serum and urine EVs. The pathogenetic mechanisms behind PSC-CCA were also described by Grimsrud and Folseraas (2019), along with methods for identifying and treating the premalignant and malignant stages of CCA in relation to PSC [12].

A CapsNet classifier was created by Swaraj, K. P. et al. (2021) to recognise the liver regions in CT scans. The CapsNet helps in instance classification through pre-processing and feature extraction phases. Different liver images from the input datasets are used to train the classifier, and test images are used to verify the classifier's accuracy [15]. Wakiya, T. et al. (2022) investigate on utilizing DL algorithms to predict early postoperative recurrence by analyzing preoperative plain computed tomography (CT) images has shown promising outcomes. A dataset comprising CT images before surgery was collected from 41 patients who underwent curative surgery for iCCA across medical areas. Using a residual convolutional neural network, a CT patch-based predictive model was developed and assessed through a fivefold cross-validation process. Early recurrence, defined as recurrence within a year post-surgical resection, was observed in 20 out of the 41 patients (48.8%). The segmented tumor area from each patient yielded 71,081 patches for analysis. The constructed ResNet model demonstrated an average training dataset accuracy of 98.2%. The summary of literature review presented in Table 1.

Table 1. Comparison of Deep Learning Approaches for Cholangiocarcinoma Detection

Study	Methodology	Dataset	Deep Learning Models	Performance Metrics	Key Findings
Buckholz et al. (2020)	CNN for CCA detection	Hyperspectral images of CCA tissue	CNN (VGG16, ResNet)	Sensitivity: 85%, Specificity: 92%	Focused on hyperspectral images, good performance in detection but struggled with specificity due to data noise.
Zhang et al. (2019)	Image classification for CCA	Multimodal pathological image dataset	CNN (InceptionV3, ResNet)	Precision: 90%, Recall: 88%	Proposed a multimodal approach but faced challenges with dataset size.
Wang et al. (2021)	Computer-aided diagnosis system	CT and MRI scans of liver cancer patients	CNN (MobileNetV2, DenseNet)	Accuracy: 89%	Focused on liver cancer, with a smaller dataset leading to overfitting concerns.
Swaraj et al. (2021)	CapsNet for liver cancer detection	CT liver images	CapsNet (Capsule Networks)	Accuracy: 98%, Sensitivity: 94%	Introduced Capsule Networks (CapsNet) for image segmentation, achieving high sensitivity.

Li et al. (2022)	Hyperspectral image segmentation	Hyperspectral CCA dataset	Transformer model with SCAT	Segmentation accuracy: 93%	Successfully improved segmentation accuracy with SCAT, but not directly applicable to full CCA detection.
Teramoto et al. (2022)	GAN for rare disease detection	Tissue samples from IIP patients	CNN with GAN-generated data	Sensitivity: 95%, AUC: 0.98	Demonstrated use of GANs for rare diseases with successful image generation for training.

3 RESEARCH METHODOLOGY

For cholangiocarcinoma diagnosis, this research applied the original "VGG19, ResNet152V2, MobileNetV2, Inception-V3, DenseNet201, and Xception" architectures. The selection of CNN architectures was based on the study by [15], which categorized the taxonomy of CNN depending on the type of architecture into seven different classes, namely; "spatial exploitation, depth, multipath, width, feature-map exploitation, channel boosting, and attention-based CNNs". From each of the category, one architecture was selected. However, there is overlap, such as ResNet falls in depth, width, and multi-path category. The methodology is illustrated in Figure 1, the data distribution is shown in Table 2, and sample images are provided in Figure 2.

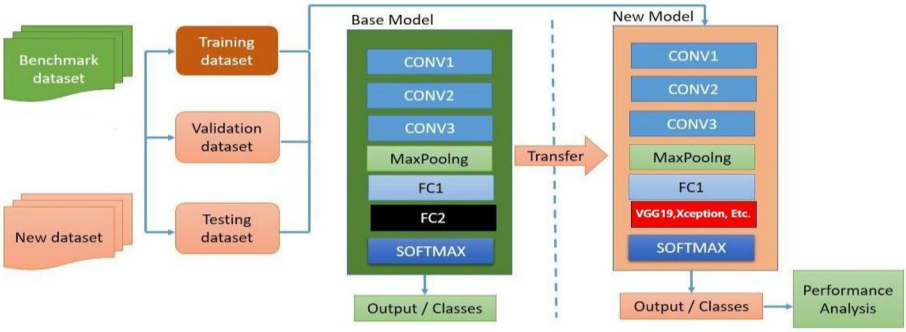

Figure 1: Research Methodology.

Table 2: Distribution of cholangiocarcinoma images

	No of Images	**Training images**	**Validation images**
Samples-Part of cancer	690	483	138
Full-Full Part of cancer	49	34	10
Normal-Without cancer part	142	99	28

Total	881	616	176

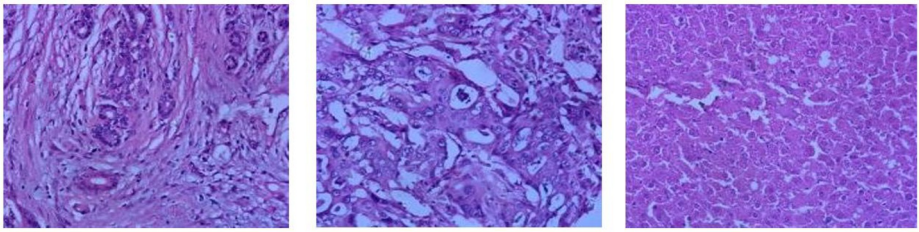

Figure 2. Example of 3 classes: Samples-Part of cancer, Full-Full Part of cancer, Normal-Without cancer part.

The multidimensional choledoch database organizes its image filenames to convey specific information about the content. These filenames encompass three distinct types of samples: Sample-samples containing partial areas affected by cancer, Full- samples portraying complete cancer areas, and Normal samples showcasing regions devoid of cancerous presence. The filename structure follows a pattern delimited by dashes, exemplified by entries like 030406-20x-roi1. The initial part, such as 030406, signifies the unique identifier for tissue specimens. The second segment, denoted by 20x, indicates the magnification level attained through the objective lens used during imaging. The pre-processing steps applied to pathological choledoch tissue RGB images are outlined in Figure 3, illustrating the sequential application of various techniques aimed at optimizing the images for subsequent analysis and diagnosis in the research.

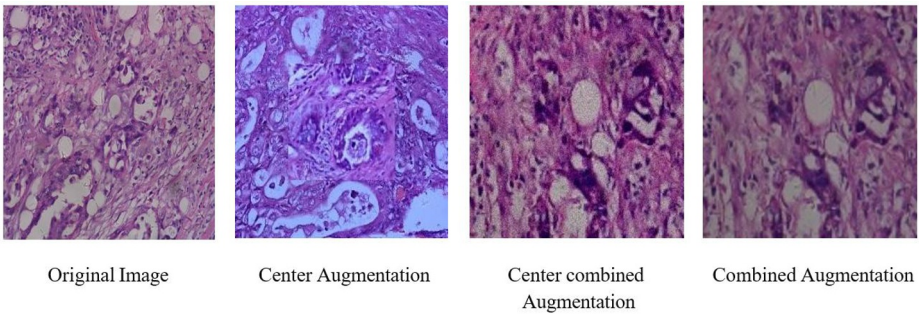

Figure 3. Results of image augmentation

3.1 Dataset

The dataset comprises of RGB images of healthy and malignant tissue from MRI. It was divided in training, validation and test sets with 881, 616 and 176 images respectively. The images were resized to 224x224 pixels, and then normalized, which could improve the stability of training. Data augmentation including rotation, flipping and zooming was performed to training set in order to add model robustness. Augmentation techniques helped mitigate the limited dataset size, but further augmentation

strategies or synthetic data generation could improve robustness. The models were trained for 250 epochs and early stopping was used if the validation performance was not better than that estimated at any time over a period of 10 successive epochs. We employed Adam optimizer with learning rate of 0.0001 and batch size of 16. Precision, Recall, F1-score, and Specificity were used to evaluate the models.

3.2 Applied Mechanism

CNN learner model was constructed using various architectures like VGG19, Resnet152V2, InceptionV3, Xception, MobileNetV2, and DenseNet201. These models underwent training using a specific dataset and were subsequently tested to assess their classification accuracy. Each of the models was trained over 250 epochs (iterations) while incorporating Early Stopping callbacks, set with a patience parameter of 10 iterations. This means that if there was no improvement in performance for 10 consecutive epochs, the training process would cease. The models underwent training using the same optimizer and were subsequently saved as .h5 files. Training durations varied: DenseNet201 took approximately 31 seconds per epoch, while ResNet152V2 and Inceptionv3 each required about 17 seconds per epoch. Within this research, standard deviation served as the chosen performance metric, as the dataset exhibited no significant imbalances. Hyperparameters were set as follows: "a dropout rate of 0.3, learning rate of 0.0001, batch size of 16, and 250 epochs". Neural networks were selected for their established success as classifiers across numerous real-world applications. The proposed system diagram is presented in Figure 4.

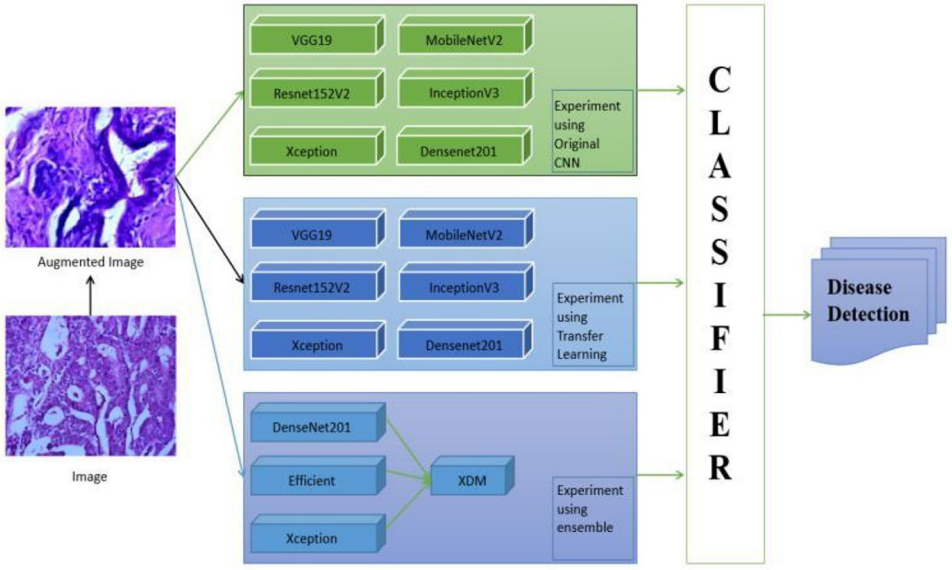

Figure 4: Proposed system diagram.

4 EXPERIMENTAL RESULTS AND DISCUSSION

The performance of six transfer learning CNN architectures is presented. DenseNet201 model achieved not only the highest training accuracy but also the highest model accuracy with the values of 99% and 93% respectively. Meanwhile, the VGG19 provides the lowest training accuracy (84%) and the MobileNetV2 provides lowest model accuracy (89%). The rest of architectures got the lowest training accuracy of 99% except the VGG19 which has 84% training accuracy. On the other hand, "VGG19, InceptionV3, Xception, ResNet152V2, and DenseNet201" produce 90% to 93% model accuracy for cholangiocarcinoma diagnosis through transfer learning [16].

Table 3 give the "Precision, Recall, F1-score, and Specificity" results of transfer learning. Resnet152 V2 architecture provides the best performance and VGG19 stipulates the worst performance. The MobileNetV2 performed mentionable lowest Recall value 91% for the identification of the Sample (Part of cancer). The test results of transfer learning also show that, the Sample (Part of cancer) is identified correctly with the most Precision, Recall and F1-score value by the Xception. In term of Normal (Without cancer) class, best recall (95%) is achieved through Densenet201and MobileNetV2 while VGG19 stipulates lowest F1-score (78%). In contrast, the Full (Full part of Cancer) is classified with 54% Precision and 31% F1-score which is the best score among all provided by Xception and MobileNetV2 respectively and 36% Recall is achieved through MobileNetV2.

Table 3. Classification Report of Transfer learning

DenseNet201	Full	Normal	Sample
Precision	17%	87%	94%
Recall	1%	96%	98%
F1-score	2%	91%	96%
Support (N)	164	470	2278
VGG19	Full	Normal	Sample
Precision	00%	97%	89%
Recall	00%	71%	100%
F1-score	00%	82%	94%
Support (N)	156	465	2195
InceptionV3	Full	Normal	Sample
Precision	54%	77%	95%
Recall	12%	94%	96%
F1-score	20%	85%	96%
Support (N)	157	453	2206
Xception	Full	Normal	Sample
Precision	00%	85%	94%
Recall	00%	89%	99%
F1-score	00%	87%	96%
Support (N)	154	450	2212
Resnet152V2	Full	Normal	Sample

Precision	36%	78%	95%
Recall	17%	93%	95%
F1-score	23%	84%	95%
Support (N)	156	455	2205
MobilenetV2	Full	Normal	Sample
Precision	27%	85%	96%
Recall	36%	96%	91%
F1-score	31%	90%	94%
Support (N)	163	453	2200

The performance of transfer learning is presented through confusion matrix. The confusion matrixes illustrate that Resnet152 V2 predict Meningioma through high TP values than any other networks and it predicts 2396 samples correctly out of 2940. Besides, VGG16 has low TP values and high FP and FN values. Regarding the No-tumor class, Densenet201outperforms others by predicting 3050 samples with correctly out of 3582. However, there are higher FP and FN values comparing to other classes. Similarly, Densenet201 overtakes others through predicting 3009 Pituitary samples accurately out of 3146 samples. In contrast, Xception shows high performance with 2610 TP values for Glioma. The Loss and Accuracy curve of Transfer learning CNN models VGG19, ResNet152V2, InceptionV3, Xception, MobielNetV2, and DenseNet201 are presented in Figure 5, Figure 6, Figure 7, Figure 8, Figure 9, Figure 10, respectively.

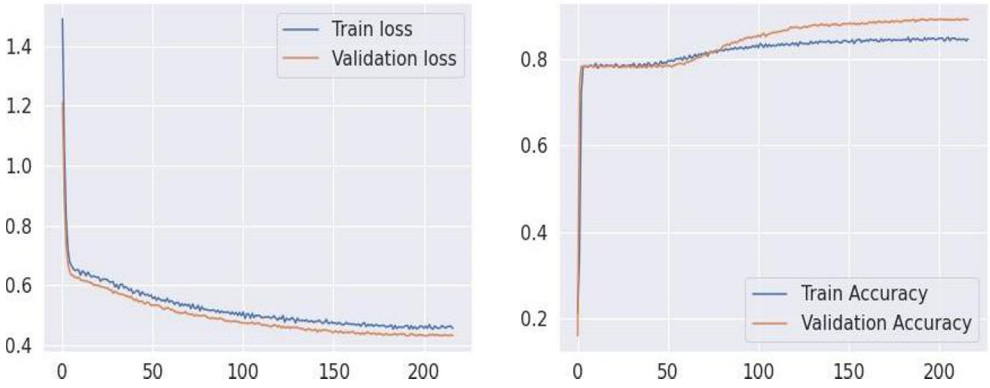

Figure 5. Loss and Accuracy curve of VGG19.

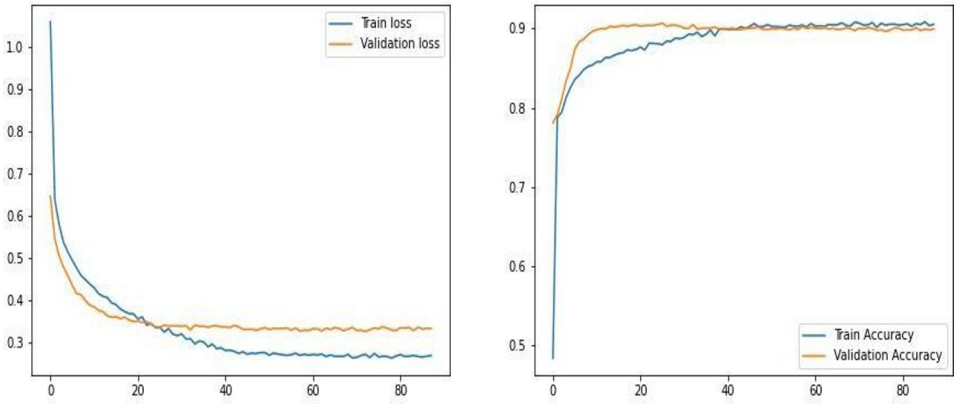

Figure 6. Loss and Accuracy curve of Resnet152V2.

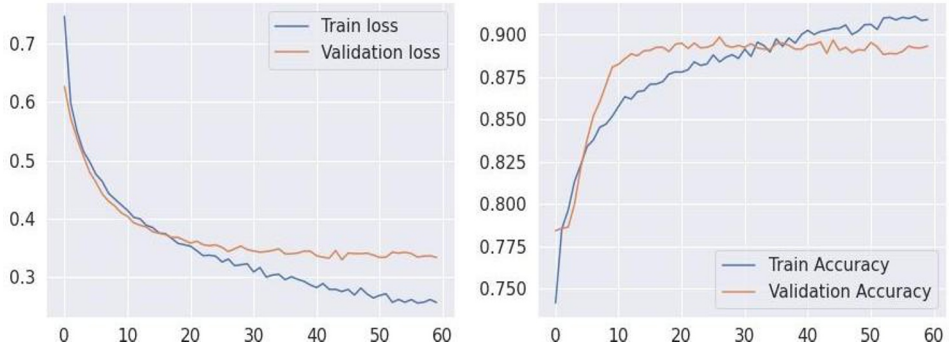

Figure 7. Loss and Accuracy curve of InceptionV3.

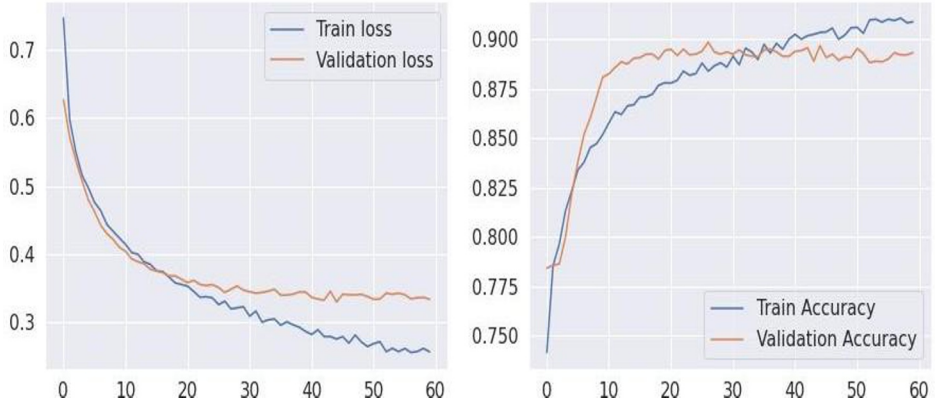

Figure 8. Loss and Accuracy curve of Xception.

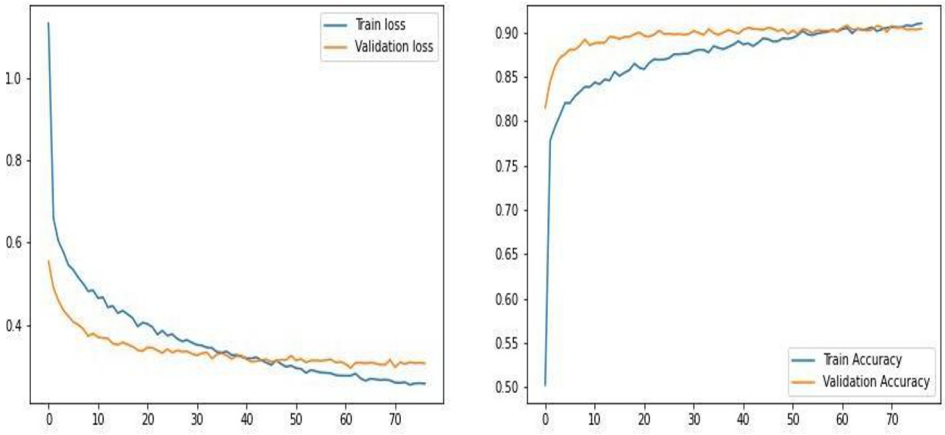

Figure 9. Loss and Accuracy curve of MobilenetV2.

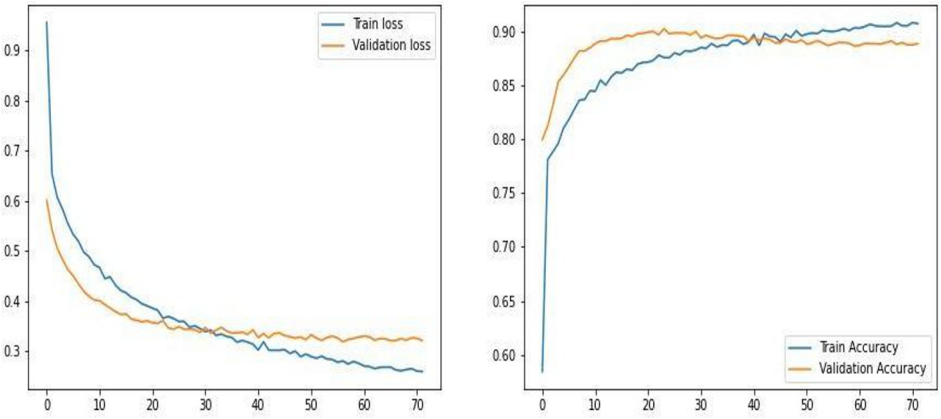

Figure 10. Loss and Accuracy curve of Densenet201.

The accuracy evaluated of appropriately classified samples total number of all samples. In term of training accuracy, DenseNet201, Xception, InceptionV3, VGG19, MobileNetV2, and Resnet152V2 have the highest value (99%). DenseNet201 exhibits the maximum value of 93% while MobileNetV2 has the minimum percentage of 89%. The rest of the architecture shows the moderate model accuracy.

5 SUMMARY, CONCLUSION, AND IMPLICATION FOR FUTURE RESEARCH

5.1 Summary of the Study

The study revealed differing accuracy rates in the classification of cholangiocarcinoma images using VGG19, Resnet152V2, InceptionV3, Xception, MobileNetV2, and

DenseNet201, all trained on the same dataset. The original DenseNet201, Xception, and InceptionV3 models displayed the highest accuracies, achieving 93%, 92%, and 91%, respectively, for the same brain cholangiocarcinoma images.
Transfer learning, a method aimed at enhancing a learner's performance by leveraging knowledge from related environments, was explored. Pinto et al. highlighted the importance of utilizing transfer learning when the source and target datasets exhibit a certain degree of similarity to avoid a decrease in performance. The study underscored the risk of negative transfer arising from dissimilarities between the target and source datasets. However, it emphasized the potential efficacy of transfer learning in effectively training deep learning models.

5.2 Conclusion

Detecting and classifying cholangiocarcinoma early on stands as a critical need for accurate diagnosis and subsequent treatment. This study's primary focus is to comprehensively assess the performance of D-CNN (Deep Convolutional Neural Network) in detecting and classifying cholangiocarcinoma. Our research indicates that employing MR-CNN (Magnetic Resonance Convolutional Neural Network) proves effective, especially when dealing with limited and potentially unclean datasets. Notably, the existing literature on cholangiocarcinoma detection is quite scarce, prompting this comparative study, which holds significant promise in enhancing cholangiocarcinoma management. Our investigation into cholangiocarcinoma classification involved evaluating various CNN models, including those utilizing transfer learning techniques. The model demonstrated promising performance, achieving an average precision of 0.885 with an inference time of 3173 milliseconds. However, the research faces several limitations that require attention in future investigations.

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