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Empowering Cancer Diagnosis: Unveiling Bladder Cancer with Advanced Deep Learning

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Abstract. *Artificial intelligence and deep learning in particular are now considered as promising methods in numerous scientific fields including medical science because the former can handle large amounts of data with non-linear relationships. Urinary bladder cancer is another frequent neoplasm that has variable histological variants and requires correct classification for the appropriate treatment tactics and prediction. This study proposed a Convolutional Neural Network (CNN) model that is accurate and simple to classifying bladder cancer, where, comparing its performance against three transfer learning architectures: These models include VGG16, InceptionV3, and MobileNetV2 for the two datasets that were used. It is seen from the experimental results that the proposed deep CNN model achieves a higher overall accuracy than the established transfer learning models which is 99. 5% in the final prediction and this makes the system suitable as a diagnostic tool for diagnosing bladder cancer.*

Keywords: *Bladder cancer; Transfer learning; Deep learning.*

1. INTRODUCTION

Bladder cancer is one of the most crucial conditions internationally affecting a large number of people and making a major contribution to cancer burden. The correct identification of its various specific histopathological subtypes plays an important role in determining the course of therapy of the disease [1].

It was identified that bladder cancer is among the most common types of cancer throughout the world and it is a significant issue for the population. The World Health Organization (WHO) captures it among the well-known ten universally prevalent cancers; from the evidence, there are about 550000 new cases annually [2]. This high incidence is therefore an indication that further efforts need to be put in coming up with accurate diagnosis and treatment plans for this disease.

They are invasive, noninvasive and normal bladder tissues which are all histopathological forms in which the disease presents itself in. All of them needs distinct treatment methods for the best results to be achieved out of the therapies administered. It is especially important for the classification of these subtypes to be accurate and reliable to target treatment decisions that include surgery, radiation therapy, immunotherapy and others, and likelihood of disease progression and recurrence [3]. Bladder cancer primarily emerges from the lining of the bladder namely urothelium and the most common type of bladder cancer is urothelial carcinoma. However, a subset of BLNAs (10–25%) presents with variant histology

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means differentiation into different types of histomorphologic form including squamous cell carcinoma, small cell carcinoma and adenocarcinoma. Another subtypes of high-grade urothelial carcinomas include micro papillary, sarcomatoid, plasmacytoid, nested and microcystic variants, these tumors diverge differentiating into squamous and glandular tissue. These variant histologies are quoted to be more aggressive, with high chances of metastasizing and are mostly unresponsive to available treatments. Several histological differences have been identified between these two types of cancer, which has raised questions over the effects of such differences on the prognosis of patients [4].

Appropriate staging of bladder cancer remains crucial for the enhancement of patient outcome, identification of high risk tumors at an early phase, and for the advancement of molecular targeted therapy. This in turn results in better survival rates and quality of people's lives who suffer from this multifaceted illness. With every year bringing new cases of bladder cancer and the progressive development of efficient diagnostic and treatment plans being an urgent necessity, improvements to the accuracy of classification methods, which may involve the application of differential deep learning algorithms, may become the key to the enhancement of the abilities of users. This evolution if achieved will improve the quality of patients suffering from bladder cancer as well as reduce the burden across the world [5]. Another type of machine learning is called deep learning with the help of extensive neural networks, it is used for searching the numerous patterns in large data. Concerning medical imaging, it is worth noting that deep learning has made many practical contributions by increasing the level of precision and speed of such processes as image segmentation, object recognition, and feature extraction within the specificity of the given area [6]. These developments are significant in the classification of bladder cancer where correct identification of the cancer type is of utmost importance when planning for the treatment to be taken [7].

This paper focuses on the use of deep learning models in bladder cancer data sets with particular focus on CNN's. It also looks at how Transfer Learning (MobileNet [8], VGG16 [9], InceptionV3 [10]) models could also be used to auto detect and extract contextual features from the medical images of importance in diagnosis and proper treatment planning. Furthermore, this work provides an extensive overview of the classification of the bladder cancer into multiple subtypes. The contributions of this study are as follows:

Proposed Deep Learning Model: We present a new DL model towards the screening of BC based on two separate data sets. These datasets are used to train the proposed architecture and also gains performance metrics and compared with other transfer learning models like MobileNet & VGG16 & etc.

Efficient Model Design: To guarantee its efficiency, the model is tested various data sets so that it indicates a wide applicability of the obtained results.

High Diagnosis Rate: The architecture that is to be developed is going to enhance the diagnostic capacity so as to ensure that, the subtypes of the bladder cancer is classified accurately.

Addressing overfitting and underfitting: The model takes into consideration problems of overfitting and under fitting than the other models leading to better performance.

The remainder of the paper is structured as follows: Section II reviews related works by various authors on the topic. Section III details the materials and methods, including an explanation of CNN layers and feedforward networks, outlining their mechanisms. Section IV covers the TreeBank dataset description, experimental setup, results, findings, and data analysis. Finally, Section V presents the conclusion and discusses potential directions for future research.

2. RELATED WORKS

Recent advancements in deep learning-based models have significantly enhanced automatic feature extraction in medical image analysis. Among these models, Convolutional Neural Networks (CNNs) are notably prominent, especially in classification tasks involving radiological data.

Ann-Christin W., et al. [11], used deep learning and traditional histology slides to try and determine the molecular subtype of muscle-invasive bladder cancer (MIBC). The 407-person dataset, The Cancer Genome Atlas Urothelial Bladder Carcinoma, was used for this analysis. ResNet, short for residual neural network, was used in the classification testing. The deep learning technique, known as mibCNN, achieved an accuracy of the ROC curve by the use of novel optimization tactics during training.

Kenny H., et al. [12], presented the AI-CALS system, which was used to divide up lesions in the bladder. The study used three different radiomics-based predictive models, a bridging method that extracts radiomics features from visual patterns, a deep learning convolution neural network (DL-CNN), and a radiomics feature-based strategy. Computed tomography (CT) scan data from both before and after treatment is used in this investigation. In the performance, the AUCs of Radiologist 1 (0.76 ± 0.08), Radiologist 2 (0.77 ± 0.07), RF-SL (0.77 ± 0.08), and RF-ROI (0.69 ± 0.08) were employed.

Mohammed K., et al. [13], provided a study on the automated bladder image analysis system (BLIAS), which utilized the CNN architectures of Inception v3 and AlexNet. The paper included images of H&E-stained slides from bladder biopsies, and the precision of these images is Inception performs better than the others, with an average accuracy of 97%; AlexNet is second with 88%, and the stacked autoencoder is third with 80%.

Audrey K. et al. [14] utilized biological classes instead of clinical classes in their study, providing a single-sample mRNA classifier. The consensus classification established a consistent framework for molecular classification, and class-specific mutations were identified using TCGA exome data.

Constantine V. et al. [15] utilized CNN for feature extraction from histology images, leveraging data provided by TCGA for training. They reported AUROC values of 0.76, specificity of 0.42, and sensitivity of 0.89. Their model utilized TIL proportion to predict FGFR23 gene mutation in bladder cancer patients, analyzing 324 genes to develop a predictive model.

Ying S. et al. [16] advocated for deep learning in automatic contouring during radiation therapy for rectal cancer. Employing two CNNs, DeepLabv3+ and ResUNet, they assigned ResUNet for OAR contouring and DeepLabv3+ for CTV contouring. Trained on original CT scans and segmentation masks, their models achieved Dice coefficients of 0.88 versus 0.87 ($P = 0.0005$) and a Surface Dice coefficient of 0.79.

Yang D., et al. [17], developed a deep learning application, utilizing CNN in particular, to accurately diagnose bladder cancer in cystoscopy images. The study collected a large number of patient images while achieving acceptable accuracy rates using the Caffe framework and the EasyDL platform. The main results were 82.9% and 96.9% accuracy rates, respectively. Application of the EasyDL model on a mobile device enabled accurate photo recognition of bladder cancer.

Atsushi I., et al. [18], the purpose of the proposed article was to objectively evaluate cystoscopy images in order to improve the diagnosis accuracy of bladder cancer. This involved using a dataset of cystoscopy pictures to create and evaluate a convolutional neural network (CNN) based tumour classifier. The trained classifier performed effectively in distinguishing tumour images from normal images, attaining high sensitivity (89.7%) and specificity (94.0%).

3. BLADDER CANCER

The urinary system sees bladder cancer as its most widespread form of cancer. Bladder cancer stands as the fourth deadliest cancer type among all tumors. Seniority rates remain high in Western nations while China now shows rising cases. Two main bladder cancer types exist based on tumor movement between bladder lining and surrounding tissues beyond the bladder walls. Treatment decisions for patients mainly depend on how far cancer has spread. Medical practitioners must use endoscopy findings together with lab test results and patient symptoms to identify between different types of bladder cancer growth. Table 1 lists the bladder cancer medical signs and Table 2 presents its tissue diagnosis with a clear separation between NTL and NST cases.

Table 1. Histopathological and Clinical features of bladder cancer.

Feature	High-Grade Non-Invasive	Low-Grade Invasive (T1)
Clinical Presentation	Hematuria, urinary symptoms	Hematuria, urinary symptoms
Histopathology	Cellular atypia, high mitotic rate, disorganized urothelium, CIS	Less cellular atypia, orderly architecture, fewer mitotic figures
Endoscopic Appearance	Flat, erythematous patches, mucosal irregularities	Papillary or nodular lesions, well-defined masses

Table 2. Differentiation of NTL and NST

Feature	No Tumor Lesion (NTL)	Non-Suspicious Tissue (NST)
Clinical Presentation	Dysuria, frequency, urgency, suprapubic pain	Asymptomatic or non-specific symptoms
Endoscopic Appearance	Diffuse erythema, edema, hemorrhagic spots, thickened mucosa, fibrosis, ulceration	Smooth, pale pink mucosa, uniform color, normal vasculature pattern

4. MATERIALS AND METHODE

4.1. MATERIALS (DATASET)

In this study, two distinct datasets as shown in Figure 1 were used to train and evaluate the proposed deep learning model for bladder cancer diagnosis. These datasets include a proprietary collection developed at Zagazig University in Egypt, and a set of endoscopic images from patients undergoing clinical procedures. The comprehensive details of these datasets are as follows:

1- Proprietary Dataset:

The research team at Zagazig University in Egypt built this exclusive dataset under IRP approval 11044-22-8-2023. This dataset consists of 2,629 pathological images categorized into three classes: non-invasive malignant, invasive malignant, and normal bladder mucosa, which serves as a standard for deep learning measurement [20].

2- Endoscopic Dataset:

The second dataset includes 1754 endoscopic images taken during Trans-Urethral Resection of Bladder Tumor procedures for 23 patients. Researchers drew their labels from medical evaluations of the tissue that surgeons removed. During endoscopy White Light Imaging (WLI) technology serves as the baseline while Narrow Band Imaging (NBI) is used when accessible. This dataset is categorized into four classes following, by the World Health Organization WHO and the International Society of Urological

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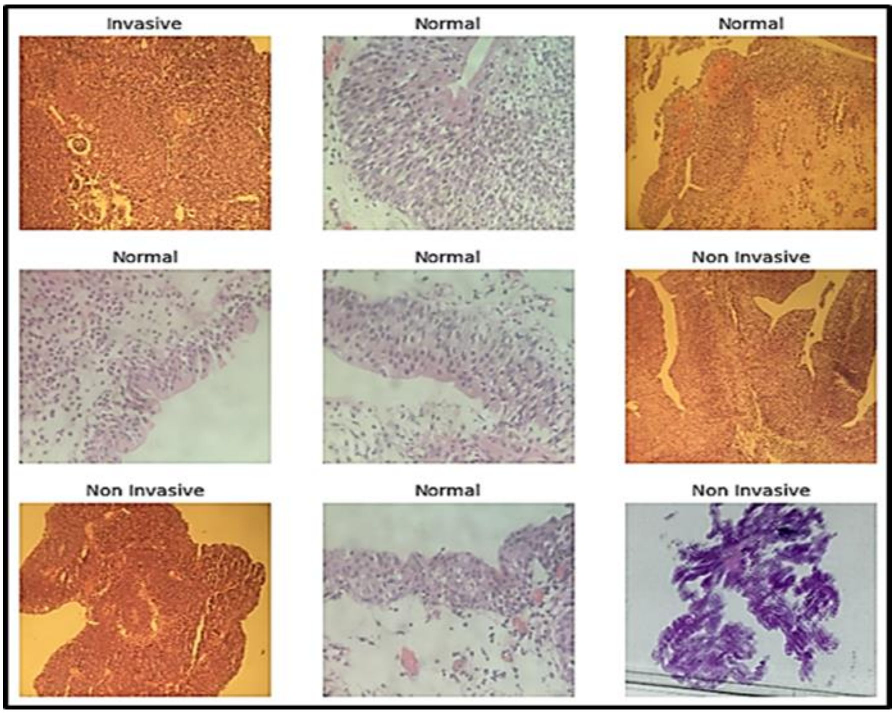
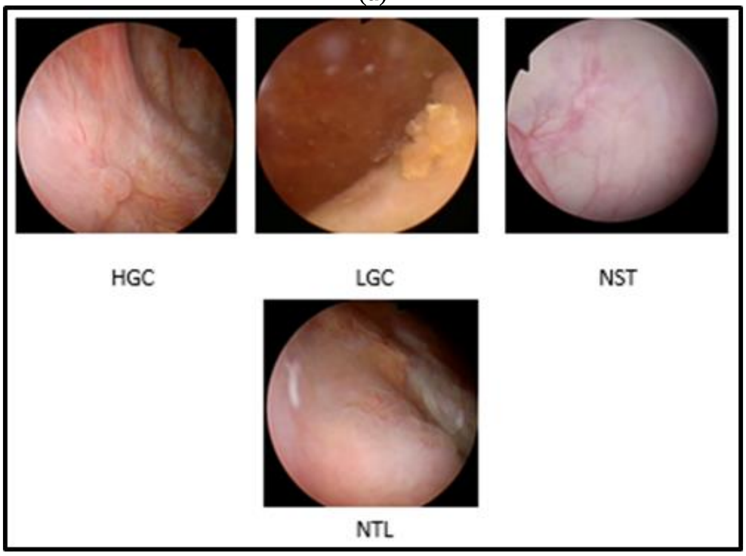
Pathology guidelines: The data set groups Bladder tissue into three main types including Low-Grade Cancer (LGC), High-Grade Cancer (HGC) with No Tumor Lesion (NTL) comprising cystitis and related inflammatory conditions plus Non-Suspicious Tissue (NST)[21].



(a)



(b)

Fig. 1. Examples of histological and endoscopic: (a) Samples of data set1 [20], (b) Samples of data set2 [21].

Table 3 categorize a dataset of cases into different classes with a corresponding number of cases in each class. Specifically, it lists two distinct data sources identified as dataset 1 and dataset 2. Each dataset contains multiple classes, each with a certain number of cases. For instance, dataset 1 includes classes like "Non-invasive", "Invasive", and "Normal" with the respective count of 660, 1178, and 454 cases,

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respectively. Similarly, dataset 2 enumerates cases under 'LGC', 'HGC', 'NTL' and 'NST' with counts of 647, 469, 134 and 504, respectively. Figure 2 shows examples of histological and endoscopic data sets, where "a" shows various histological slides as anexamples of data set1, . These slides include different types of tissue sections stained with various dyes, such as haematoxylin and eosin (H&E) and other staining methods. Histological images are crucial for examining the microscopic structure of tissues, aiding in the diagnosis and study of diseases, particularly cancer. Endoscopic images as an examples of data set2 are shown in (b). These images are captured using an endoscope, a specialized medical instrument equipped with a camera allowing internal visualization of an organ or tissue. Endoscopic imaging is commonly used for diagnosing and monitoring conditions within the gastrointestinal tract, respiratory system, and other internal structures. Both types of data sets are vital in medical research and diagnostics, providing comprehensive views from the cellular to the organ level. The datasets undergo pre-processing, including image scaling by normalization to [0, 1], before being divided into subsets for training, validation, and prediction.

Table 3. Classification of cases in dataset 1 and dataset 2 across multiple classes.

Material	Class	No. of Cases
Dataset 1	Non invasive	660
	Invasive	1178
	Normal	454
Dataset 2	LGC	647
	HGC	469
	NTL	134
	NST	504

4.2. METHODS (THE SUGGESTED MODEL)

The proposed system utilizes a Deep Neural Network structured on CNN architecture and is juxtaposed with transfer learning models like MobileNetV2, Inception V3, and VGG16 to determine the optimal system for diagnosing bladder cancer. The sequential stages of the suggested system are delineated in Figure 2, encompassing pre-processing, training, validation, testing, and result interpretation for efficient classification of medical datasets.

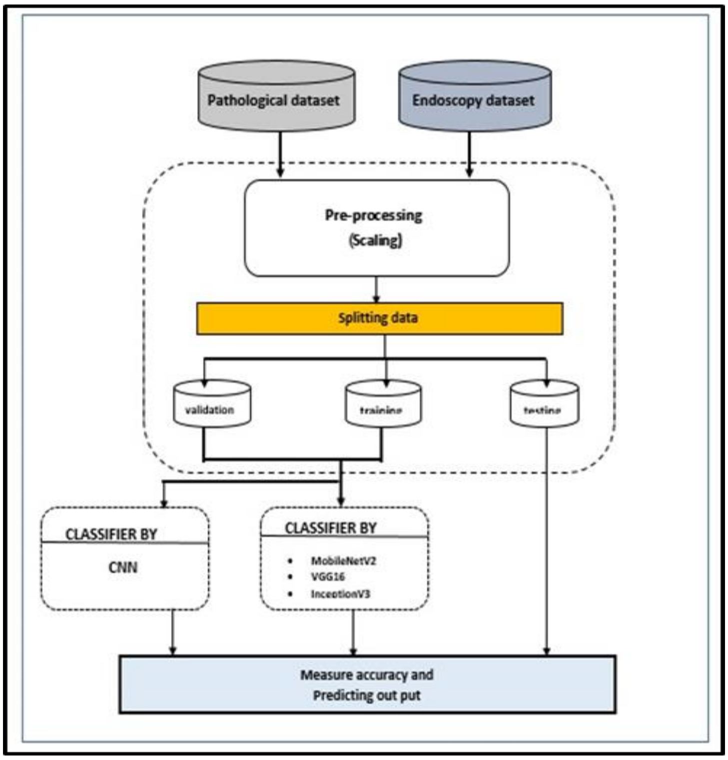

Fig. 2. The proposed system.

1) Convolutional Neural Network

A convolutional neural network (CNN) is a type of deep learning network inspired by artificial neural networks. CNNs are typically structured as a series of stages composed of different layers. Essentially, a CNN is a multi-layer network consisting of five main layers: the input layer, convolutional layer, pooling layer, fully connected layer, and output layer. The convolutional layer contains multiple feature maps, which are generated by convolving the convolution kernel from the previous layer, as follows [19]:

$$X^{\#} = f[\sum_{i\in M_j}(X^{l-1} * K_{ij}^{l} + b_j^{l})] \qquad (1)$$

Where:

M_j: Represents the input image.
$X\#$: the j[th] features map of the l[th] layer.
*: the convolution operation.
X^{l-1}: Is the i[th] features map of the $l-1$ layer.
K_{ij}^{l}: the filter connecting the jth feature map of the l[th] layer and i[th] features map of the $l-1$ layer.
b_j^{l}: Is the bias.

The CNN model employed in this study comprises a series of layers defined using the Sequential class. Table 4 depict the detailed architecture of the proposed Deep Neural Network based on CNN, emphasizing the sophisticated network design tailored for precise and dependable bladder cancer classification. The layer breakdown includes [19]:

- Rescaling: Normalizes input pixel values to [0, 1] by dividing by 255.
- Conv2D: Applies 2D convolution with 16 filters, a 3x3 kernel, 'same' padding, and ReLU activation (f(x) = max (0, x)) to extract 16 features.
- MaxPooling2D: Performs max pooling to down sample feature maps from the previous layer.

- Additional Layers: Adds two more Conv2D and MaxPooling2D layers with 32 and 64 filters to capture more complex features.
- Flatten: Converts the output from the previous layer into a 1D vector for the fully connected layers.
- Dense: Creates a fully connected layer with 128 units and ReLU activation to identify complex patterns, followed by another Dense layer with num_classes units for final classification using a SoftMax classifier:

$$\sigma(z)_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_J}} \qquad (2)$$

Table 4. The proposed CNN layers and parameters.

Layer	Input Size	Output Size	Filter Size (FS)	No. of Parameters
Input	224x224x3	224x224x3	-	0
Rescaling	224x224x3	180x180x3	-	0
Conv2D	180x180x3	180x180x16	3x3	448
MaxPooling2D	180x180x16	90x90x16	-	0
Conv2D	90x90x16	90x90x32	3x3	4640
MaxPooling2D	90x90x32	45x45x32	-	0
Conv2D	45x45x32	45x45x64	3x3	18496
MaxPooling2D	45x45x64	22x22x64	-	0
Flatten	22x22x64	30976	-	0
Dense	30976	128	-	3965056
Dense	128	3	-	387

2) Transfer Learning:

Transfer learning is a machine learning technique where a model developed for one task is reused as the starting point for a model on a second task. This is particularly useful when you have a limited amount of training data for the second task [23]. Transfer learning is particularly useful in computer vision tasks, where the low-level features (e.g., edges, shapes) learned by a CNN model on a large dataset like ImageNet can be effectively reused for a wide variety of image classification, object detection, or segmentation tasks.

1- VGG16 is a deep learning model that is categorized under the Convolutional Neural Network or the CNN family of model and it was created by researchers at the University of Oxford's Visual Geometry Group (VGG). It was introduced in 2014 and has since then been widely used for transfer learning in tasks concerning computer vision. It is evident that VGG16 has a total of 16 weight layers in its architectures: 13 convolutional layers, 5 pooling layers and 3lrntotally fully connected layers.
2- MobileNetV2 is a convolutional neural network which was designed rating a Google in 2018. It is a modified version of the MobileNet structure and is optimal for usage in mobile as well as the embedded systems [8].
3- Inception-v3 is the new improvement from the Goggle original architecture known as GoogleNet or Inception-v1 network. It was proposed in 2015 and it is one of the most complex Inception-based model in group of Inception models. Inception-v3 contains a total of 48 layers which does not include the final average pooling layer as well [10].

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5. EXPERIMENTAL RESULT AND ANALYSIS

The proposed deep learning algorithms (CNN, VGG16, InceptionV3, and MobileNetV2) were assessed using two datasets: 2,629 pathological images and 1,754 endoscopic images, with each dataset comprising 70% of the total data. The data was split into 70% for training, 15% for validation, and 15% for testing to evaluate the model's generalizability and prediction ability on unseen data. A random selection of training and validation images was used for better evaluation over 10 epochs. The experiments were conducted on a personal computer using Python on a Windows 10, 64-bit operating system. Performance metrics, specifically accuracy, were employed to assess the models as shown in Eq. (3). The highest accuracy achieved by CNN was 99.78%, with a training accuracy of 98.04% using the endoscopy dataset, as shown in Table 5. For the second dataset, the best accuracy achieved was 98.5% by CNN, as detailed in Table 6. Additionally, there was no significant difference between training and validation accuracy when using CNN, indicating no overfitting, as shown in Fig 3, and 4 for both datasets. In contrast, methods like VGG16 showed a clear difference between training and validation accuracy, indicating overfitting, as seen in Fig. 5.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

Table 5. The result of dataset 1 (endoscopy) using CNN, InceptionV3, VGG16, and MobileNetV2.

Method	Training		Validation		Precision	Sensitivity (Recall)	F1 Score
	Loss	Accuracy	Loss	Accuracy			
InceptionV3	5.00	0.97	5.35	1.00	0.93	0.93	0.93
VGG16	0.02	0.92	0.01	1.00	0.92	0.92	0.92
MobileNetV2	2.45	0.95	1.92	1.00	0.94	0.94	0.94
Proposed CNN	0.06	**0.98**	0.01	**0.99**	0.97	0.97	0.97

Table 6. The result of dataset 2 (pathological images) using CNN, InceptionV3, VGG16, and MobileNetV2.

Method	Training		Validation		Precision	Sensitivity (Recall)	F1 Score
	Loss	Accuracy	Loss	Accuracy			
InceptionV3	0.11	0.96	0.93	0.93	0.99	0.94	0.96
VGG16	0.22	0.93	0.92	0.92	0.95	0.95	0.95
MobileNetV2	0.00	0.97	0.94	0.94	0.89	0.90	0.90
Proposed CNN	**0.04**	**0.98**	0.97	0.97	**0.98**	**0.97**	**0.94**

The results in Tables 5 and 6 compare the performance of InceptionV3, VGG16, MobileNetV2, and the proposed CNN across training and validation phases. The proposed CNN consistently achieves a strong balance between low training loss and high accuracy, outperforming the other models in F1 score (0.97) on both datasets, indicating superior generalization and adaptability. While VGG16 shows low training loss and high accuracy, it may overfit, and MobileNetV2 demonstrates good precision but lower sensitivity. InceptionV3 performs steadily but is surpassed by the proposed CNN in precision and F1 score. These findings emphasize the robustness and versatility of the proposed CNN across varied datasets.

To address overfitting and under fitting, we implemented several techniques, including dropout regularization, data augmentation (e.g., rotation, flipping, and scaling), early stopping, and L2 regularization. Additionally, k-fold cross-validation was used to ensure robust performance across data subsets.

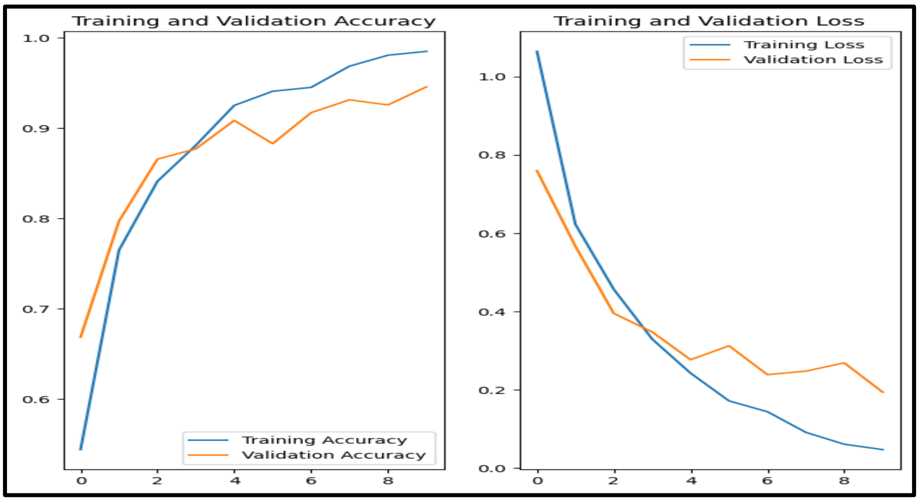

Fig. 3. Comparison of training and validation accuracy for the proposed CNN on dataset 1.

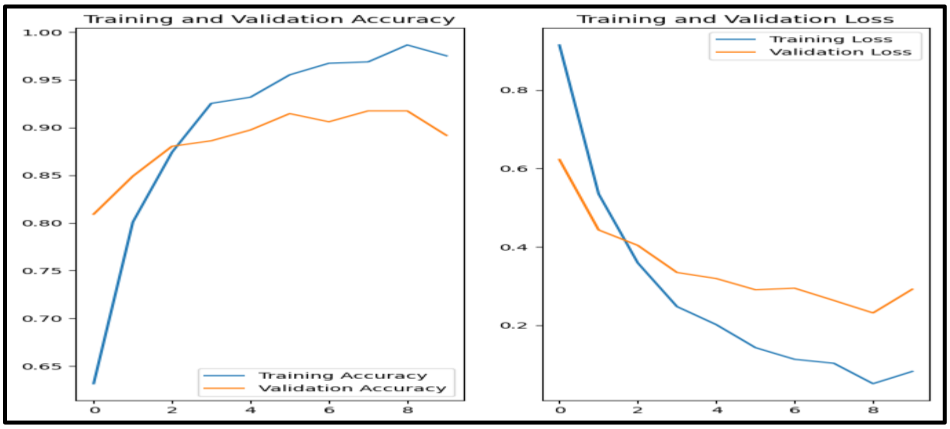

Fig. 4. The difference between training and validation accuracy for the proposed CNN on dataset 2.

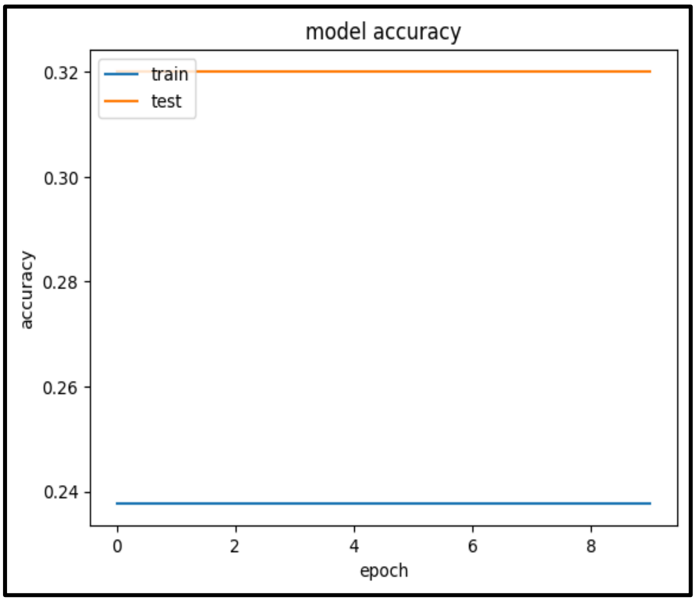

Fig. 5. Discrepancy between training and validation accuracy for VGG16.

6. CONCLUSIONS

The paper presents a deep learning model for accurately classifying bladder cancer subtypes, which is crucial for effective treatment planning and prognosis. The proposed Convolutional Neural Network (CNN) model is introduced as an efficient and reliable tool for bladder cancer diagnosis. A comparative performance analysis was conducted between the proposed CNN model and three state-of-the-art transfer learning architectures: These include VGG16, InceptionV3, and new MobileNetV2. From the experimental results it was realized that our proposed CNN model attained the best overall accuracy of 99%. Further, in the final prediction process, just 5% of the intuition was incorporated into the algorithm. The study also faced problems of both overfitting and underfitting and tried to avoid them while creating the model which has the same effectiveness when used with different datasets. The simple structures of CNN architecture allowed for extraction of features within the medical images of cognitive and intricate natures in order to improve the understanding of clinicians. The outcomes of this study can be added as a reference to the research promoting the application of state-of-the-art deep learning methodologies in medical image comprehension and especially in classification of complicated types of cancer such as bladder cancer. It may follow the expansion of the model and the investigation of the applicability of the data in larger datasets and including other populations, or including the integration of the data into practice strategies, and applying it to patient care in the future research areas. All in all, all the deep learning algorithms have some useful features for the classification of bladder cancer. Specifically, it is worthwhile to point the attention to custom CNNs as they demonstrated high accuracy and comparatively low computational costs that allow using them for most of medical imaging tasks. The hi-accuracy models such as VGG16 and InceptionV3 can however be considered better where a lot of computation power can be afforded and highest possible marginal improvement obtained. MobileNetV2 is perfect suitable for applications which requires real time performance. To ensure practical application in clinical settings, our model must seamlessly integrate with electronic health record (EHR) systems and be user-friendly for clinicians. Enhancing model interpretability through visualization techniques like Grad-CAM is crucial for building trust. Additionally, compliance with regulatory standards and ethical guidelines is essential for safe implementation. Extensive validation on multi-institutional clinical datasets will ensure the model's reliability, while addressing resource and computational constraints will facilitate deployment in diverse healthcare environments.

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