BenchCouncil Transactions on Benchmarks, Standards and Evaluations 4 (2024) 100174

Contents lists available at ScienceDirect

BenchCouncil Transactions on Benchmarks, Standards and Evaluations

journal homepage: www.keaipublishing.com/en/journals/benchcouncil-transactions-onbenchmarks-standards-and-evaluations/

Enhanced deep learning based decision support system for kidney tumour detection

Taha ETEM [a,*], Mustafa TEKE [b]

[a] Cankkiri Karatekin University, Faculty of Engineering, Computer Engineering, Cankiri, Turkey

[b] Cankkiri Karatekin University, Faculty of Engineering, Electrical-Electronics Engineering, Cankiri, Turkey

ARTICLE INFO

Keywords:
Kidney cancer
Image processing
Decision support system
Deep Learning

ABSTRACT

This study presents a high-accuracy deep learning-based decision support system for kidney cancer detection. The research utilizes a relatively large dataset of 10,000 CT images, including both healthy and tumour-detected kidney scans. After data preprocessing and optimization, various deep learning models were evaluated, with DenseNet-201 emerging as the top performer, achieving an accuracy of 99.75 %. The study compares multiple deep learning architectures, including AlexNet, EfficientNet, Darknet-53, Xception, and DenseNet-201, across different learning rates. Performance metrics such as accuracy, precision, sensitivity, F1-score, and specificity are analysed using confusion matrices. The proposed system outperforms different deep learning networks, demonstrating superior accuracy in kidney cancer detection. The improvement is attributed to effective data engineering and hyperparameter optimization of the deep learning networks. This research contributes to the field of medical image analysis by providing a robust decision support tool for early and rapid diagnosis of kidney cancer. The high accuracy and efficiency of the proposed system make it a promising aid for healthcare professionals in clinical settings.

Introduction

Kidney cancer, also known as renal cancer, is a serious and potentially life-threatening disease that affects thousands of people worldwide each year. Exploring the nature of kidney cancer, its causes, symptoms, diagnosis, treatment options, and ongoing research efforts are one of the most important research topic in nowadays [1].

Kidney cancer primarily develops in the renal cells, which line the small tubes within the kidneys. The most common type is renal cell carcinoma (RCC), accounting for about 90 % of all kidney cancers [2]. According to global statistics, kidney cancer is among the top 10 most common cancers in both men and women, with a higher incidence in developed countries. The exact cause of kidney cancer remains unknown, but several risk factors have been identified as follows [3]. The risk increases with age, with most cases diagnosed in people over 50. Tobacco uses significantly increases the risk of developing kidney cancer. Excess body weight is associated with a higher kidney risk. High blood pressure may contribute to kidney cancer development. Certain inherited genetic conditions can increase susceptibility. Long-term dialysis patients have a higher risk [4] and certain chemicals, like trichloroethylene, may increase risk [5].

Early-stage kidney cancer often presents no symptoms. As the tumour grows, potential signs may include; blood in urine (hematuria), persistent pain in the side or lower back, unexplained weight loss, fatigue, Fever not associated with an infection and Anemia [6]. Diagnosis of kidney cancer typically involves a combination of methods; physical examination, imaging tests (CT scans, MRIs, ultrasounds), blood and urine tests and if definite results cannot be obtained with all these methods, it is necessary to apply Biopsy. Recent advancements in medical imaging and the application of artificial intelligence, particularly deep learning algorithms, have significantly improved the accuracy and speed of kidney cancer detection [7]. The prognosis for kidney cancer varies greatly depending on the stage at diagnosis. Early detection significantly improves survival rates. The five-year survival rate for localized kidney cancer (confined to the kidney) is about 93 %, but this drops to about 17 % for cases where the cancer has spread to distant parts of the body [8]. Therefore, early diagnosis of kidney cancer is very important, like all other types of cancer.

In the early years, machine learning algorithms were used for prediction systems [9,10]. However, deep learning methods have been developed to make predictions directly from images [11]. Deep learning techniques have emerged as powerful tools for detecting kidney cancer

* Corresponding author.
E-mail address: tahaetem@karatekin.edu.tr (T. ETEM).

https://doi.org/10.1016/j.tbench.2024.100174
Received 7 August 2024; Received in revised form 5 September 2024; Accepted 5 September 2024
Available online 11 September 2024

in medical imaging [12]. These advanced artificial intelligence methods, particularly convolutional neural networks (CNNs), can analyse CT scans, MRI images, and ultrasounds to identify potential tumours with high accuracy [13]. By training on large datasets of labelled kidney images, deep learning models learn to recognize subtle patterns and features associated with cancerous growths. This approach offers advantageous of improved accuracy and reduced false positives, faster analysis of medical images, potential for earlier detection of small or atypical tumours and assistance to radiologists in their diagnostic workflow.

In this work, a deep learning-based kidney cancer detection system is designed to contribute faster diagnosis, higher accuracy and comparison of deep learning systems. First of all, enhanced deep learning system applied on a relatively large dataset that diagnoses very quickly after completing the training on the dataset. The proposed system is more successful than all studies in the literature and achieved classification success of over %99 with the help of data pre-processing and hyper-parameter tunings. Finally, the superiority of the study is shown by comparing it with similar studies.

Related works

Kidney cancer, known as renal cell carcinoma (RCC), represents a prevalent type of cancer originating in the renal organs. Conventional diagnostic techniques, like imaging modalities and biopsies, often face constraints in terms of accuracy and effectiveness. The emergence of deep learning, a subset of artificial intelligence, has significantly transformed medical diagnostics by introducing innovative improvements in the recognition and categorization of renal cancer. This article investigates the application of deep learning in the detection of renal cancer, focusing on its methodologies, advantages, and challenges.

Deep learning systems, notably convolutional neural networks (CNNs), are heavily utilized in the analysis of medical images [14]. Because their ability to operate directly on raw image data is quite high [15]. Trained on vast assortments of annotated medical pictures, these structures can recognize patterns and abnormalities linked to renal cancer. Deep learning is utilized in the examination of computed tomography (CT) and magnetic resonance imaging (MRI) scans. Approaches for ameliorating pictures, like Contrast Limited Adaptive Histogram Equalization (CLAHE) and Contrast Stretching, boost the quality of these scans, thereby amplifying the accuracy of tumor recognition and categorization[16].

The incorporation of profound learning into the identification of renal carcinoma presents a multitude of benefits, such as enhanced accuracy. These structures have showcased efficacy levels similar to that of medical imaging specialists in identifying renal neoplasms, thereby diminishing the incidence of incorrect identifications [17]. Automated examination of medical images decreases the duration needed for diagnosis, enabling timely clinical judgments. Advanced learning advances non-destructive diagnostic methods, lessening the necessity for tissue samplings and their linked hazards. Furthermore, through identifying genetic indicators and tumor subgroups, advanced learning assists in formulating individualized treatment tactics for individuals [18]. The diagnosis of kidney cancer using deep learning faces several challenges, with one major hurdle being the need for carefully annotated datasets to train these models. Creating and annotating such datasets is both time-consuming and costly. The lack of transparency in deep learning models makes it difficult to understand how they make decisions, which complicates the process of validating and accepting them for clinical use. The training of deep learning architectures demands substantial computational capabilities and resources, which may not be readily accessible in all healthcare environments. Ensuring the generalizability of models across diverse patient cohorts and imaging protocols is crucial for broad clinical adoption [19,20].

Gujarathi et al. provides a comprehensive survey of the application of machine learning and deep learning algorithms in kidney cancer analysis. It highlights various deep learning models, particularly convolutional neural networks (CNNs), that have achieved radiologist-level performance in diagnosing kidney cancer [17].

Lu et al. employs a Deep Q-Network (DQN) to combine reinforcement learning with deep neural networks for identifying potential risk genes associated with clear cell renal cell carcinoma (ccRCC). The study highlights the integration of genetic factors in cancer diagnosis using deep learning and uses HPRD dataset [21].

Yanto et al. examines the impact of Contrast Limited Adaptive Histogram Equalization (CLAHE) on the classification of kidney tumours using CT scans. The enhancement technique significantly improves the accuracy of deep learning models in diagnosing kidney cancer and get % 99.12 accuracy [22].

Uhm et al. proposes a Lesion-Aware Cross-Phase Attention Network (LACPANet) for renal tumour subtype classification using multi-phase CT scans. The network focuses on lesion characteristics across different phases to enhance subtype classification accuracy. Authors use Seoul St Marry Hospital CT image dataset and get %94,26 accuracy [23].

Abdulwahhab et al. discusses various deep learning applications in medical imaging, with a focus on lung and skin cancer in the review article. It highlights how deep learning models, such as convolutional neural networks (CNNs), have improved diagnostic accuracy. They found significant advancements in the literature in the accurate detection and classification of lung and skin cancers [24].

Rossi et al. explored the benefits of risk-stratified screening for kidney cancer. Their research indicates that personalized screening protocols, based on individual risk assessments, can significantly enhance early detection rates. This approach may involve genetic, environmental, and lifestyle factors [25].

Yang et al. developed novel near-infrared fluorescent dyes for optical imaging of kidney cancer. These dyes specifically target cancer cells, allowing for more precise detection in both preclinical and clinical settings. This method could revolutionize the visualization of kidney tumours during surgery [26].

Tuncer and Alkan developed a decision support system for detecting renal cell cancer using machine learning algorithms. This system can analyse medical images and clinical data to assist radiologists in identifying kidney tumours more accurately. The accuracy of the work is % 92 with SVM classifier [27].

Although all the studies have achieved success in line with their objectives, there are some shortcomings. First of all, the low accuracy rate in some studies is a deficiency, especially considering that 50 % success is achieved even in the case where no learning is performed in classification processes consisting of 2 classes. Secondly, the low number of medical images reduces the reliability of the systems. Finally, in some studies, it has been observed that the use of a single network and the tuning of hyperparameters by default reduces the system performance. In order to overcome all these deficiencies, it is tried to show the stability of the system by comparing different networks with each other as well as comparing with the studies in the literature. The hyper-parameters with the highest performance of the networks at different learning rates were optimised to obtain the highest accuracy rates in the literature.

Kidney medical scan classification dataset

Medical Scan Classification Dataset that includes kidney images with tumour and healthy kidney images, can be found available online at Kaggle [28]. Dataset contain 5000 medical images of healthy patients and 5000 medical images of kidney tumour detected patients. When the images with a healthy image in Fig. 1 and a tumour detected in Fig. 2 are examined, it is seen that it is very difficult for non-experts to detect this tumour.

As in the examples, other than horizontal section images out of a total of 10,000 images were first removed from the dataset. All of the images have 512 × 512 pixels resolution. After deleting the vertical

Fig. 1. Healthy Medical Image of a Patient.

Fig. 2. Tumour Detected Medical Image of a Patient.

versions of the same images, the study was carried out with a total of 3251 healthy images and 3152 tumour images and all of the images are resized to 224 × 224 pixels for the efficiency of deep learning networks. Since vertical angle images are images of the same patients and reduce the success of the predictive system, it was deemed appropriate to perform training and testing only with horizontal section images. An example of removed vertical angle images is shown in Fig. 3.

Fig. 3. Vertical Angle Image Example in the Dataset.

Materials and method

In order to establish a successful system, classification was first carried out using different deep learning structures. AlexNet, EfficientNet, Darknet-53, Xception, DenseNet-201 networks offered the best performance for the proposed system.

AlexNet is considered the model that started the deep learning revolution and holds an important place as one of the cornerstones of modern artificial intelligence research. The most important factor in this progress was the emergence of GPU designs and computational operations. AlexNet is an important model in the field of deep learning and image recognition. Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton worked to develop AlexNet in 2012, which gained significant recognition for winning the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) competition. AlexNet, with its 8 layers consisting of 5 convolutional layers and 3 fully connected layers, is widely recognized as a groundbreaking model that effectively showcased the power of deep learning. The incorporation of the ReLU activation function in AlexNet led to improved learning speed and efficiency. To prevent overfitting, AlexNet utilizes the dropout technique, which enhances the model's generalization by randomly deactivating specific neurons. Additionally, AlexNet leverages GPU parallel processing to optimize training on large datasets, resulting in enhanced speed and efficiency[29].

EfficientNet is created by Google and it presents an innovative strategy for scaling Convolutional Neural Network (CNN) architectures. The unique scaling technique of this model adjusts the width, depth, and resolution of various CNN models with great skill. EfficientNet achieves higher accuracy using fewer parameters and less computational resources. The EfficientNet series includes models ranging from B0 to B7, with B0 being the most compact and fastest, and B7 being the largest and most powerful. In our study, we used the EfficientNet-B0 model as the foundation, with the other versions being scaled adaptations of it. Compared to other popular CNN models, EfficientNet provides better accuracy and requires less computational resources, especially in evaluations using the ImageNet dataset. These advantages have made EfficientNet a preferred choice for both academic research and industrial applications. The innovative scaling methodology and remarkable performance of EfficientNet render it exceptionally effective for a diverse array of deep learning assignments [30].

The Darknet-53 is a key CNN structure used in the YOLOv3 algorithm, developed by Joseph Redmon and Ali Farhadi. Known for its outstanding performance in object recognition tasks, the Darknet-53 consists of 53 layers, enabling it to capture more complex features and achieve higher accuracy. To build a more profound network, Darknet-53 incorporates Residual Blocks inspired by the ResNet architecture. These blocks effectively address the issue of vanishing gradients in deep networks by using bypass connections, making it easier to train deeper models. In comparison to its predecessor, Darknet-19, Darknet-53 offers improved accuracy and increased Frames Per Second (FPS) efficiency.. Consequently, YOLOv3, which is constructed on Darknet-53, excels in executing prompt and effective object recognition [31].

Xception, short for "Extreme Inception," is a system designed to improve the structure of Convolutional Neural Networks (CNNs) in deep learning. Created by François Chollet and introduced in 2017, Xception builds upon Google's Inception framework and introduces significant improvements. It employs depthwise separable convolutions to enhance the efficiency of the Inception framework, reducing computational costs while improving model accuracy. Xception represents a revolutionary approach to enhancing both efficiency and accuracy in deep learning frameworks, combining the strengths of the Inception framework with the benefits of depthwise separable convolutions to create faster and lighter models [32].

DenseNet-201 stands out as a version of the Dense Convolutional Network (DenseNet) structure, specifically distinguished by its 201 layers. The team of Gao Huang, Zhuang Liu, Laurens van der Maaten, and Kilian Q. Weinberger introduced DenseNet-201 in 2016, with a focus on improving information flow and enhancing gradient propagation through closely connected layers. This design ensures that each layer receives input from all previous layers, promoting weight reuse and improved information flow. The primary use of 3×3 filters in DenseNet-201 helps to reduce computational costs. Additionally, bottleneck layers in the form of 1×1 convolutional layers are integrated to further streamline computations and minimize parameter usage. Transition layers, consisting of a 1×1 convolutional layer and a 2×2 average pooling layer, are incorporated to connect dense blocks and manage dimensions. The output of each layer in DenseNet is impacted by a specific growth rate, ensuring efficient and effective network performance. This dictates how many channels each layer's output contributes. In DenseNet-201, the growth rate is typically set as 32. Dense connections among layers enable gradients to propagate more smoothly, thus mitigating the vanishing gradient issue. Due to dense connections, superior performance can be attained with fewer parameters. This enables weights to be reused and renders the model more concise. DenseNet excels in various computer vision tasks, such as image categorization and object recognition, providing high accuracy and efficiency. [33]. DenseNet-201, specifically, is preferred in scenarios that require accurate and effective deep learning architectures. It attained the highest accuracy level in the research.

A crucial element in network performance is the acquisition speed, a hyperparameter that governs the degree to which weights are modified during the instruction of a machine learning model. The speed of acquiring information specifically controls how much the weights change at each step of the instructions. Setting an appropriate acquisition speed allows the model to learn quickly and effectively, while an incorrect speed can slow down the learning process. Improvement algorithms like gradient descent adjust the model's weights based on the loss function's derivative, and the acquisition speed determines the degree of these adjustments. This highlights the acquisition speed's importance as a critical parameter in training deep learning models. A too small acquisition speed can slow down the training, while a too large speed can cause instability. Applying different optimization techniques to fine-tune the acquisition speed leads to a more efficient and effective training process [34].

Network performance metrics

A confusion matrix is a table used to assess the performance of classification algorithms by comparing the predicted class labels to the real class labels. It is particularly useful for dataset with multiple classes. The confusion matrix is comprised of four key components:

1. True Positives (TP): The number of instances correctly classified as positive.
2. True Negatives (TN): The number of instances correctly classified as negative.
3. False Positives (FP): The number of instances incorrectly classified as positive (Type I error).
4. False Negatives (FN): The number of instances incorrectly classified as negative (Type II error).

An Example of the Confusion Matrix is shown in Table 1.

To evaluate the confusion matrix, it is necessary to calculate various performance metrics. The metrics can be summarized as follows:

1. Accuracy: Proportion of samples that the model predicted correctly.
2. Precision: It shows how many of the positive predictions are actually positive.
3. Recall (Sensitivity or True Positive Rate): It shows how many of the true positives were predicted correctly.
4. F1-Score: It is the harmonic mean of Precision and Recall. It is a balanced performance measure.
5. Specificity (True Negative Rate): It shows how many of the true negatives were predicted correctly.

The use of different metrics is important in decision support systems such as cancer prediction in the study. For example, if healthcare professionals are required to examine medical images more carefully, especially those containing tumours, the Recall parameter used here will show how high the tumour detection rate is.

Proposed network designs

Flow chart of the proposed prediction system is shown in Fig. 4. Firstly, Kidney images were extracted from the dataset. Then, all medical images were resized to the same size and images with errors and low resolutions were deleted. Since there are both horizontal and vertical angle images of the same patient in the dataset and since it is difficult to detect most kidney tumours in vertical angle images, these images were excluded. It was also tested with deep learning systems that it is difficult to detect tumours from vertical angled images, and it was determined that vertical angled images decreased the success in the training of all networks.

After completing all the operations on the dataset, a balanced dataset containing 6404 images with approximately equal number of tumour and healthy images was obtained. The obtained dataset was randomly divided as 75 % training and 25 % test. Then, the most successful 5 different networks are shown in the study results according to the validation results by training on many deep learning networks. Also, hyperparameter tuning plays a crucial role in optimizing deep learning networks. The choice of optimizer and loss function significantly impacts model convergence and performance. Learning rate, a key hyperparameter, influences the speed and stability of training; too high a rate may cause overshooting, while too low a rate can lead to slow convergence. Batch size affects both training speed and generalization, with larger batches potentially offering more stable gradients but at the cost of memory. The number of epochs determines how many times the

Table 1
An example of confusion matrix.

	Real Positives	Real Negatives
Predicted Positives	TP	FP
Predicted Negatives	FN	TN

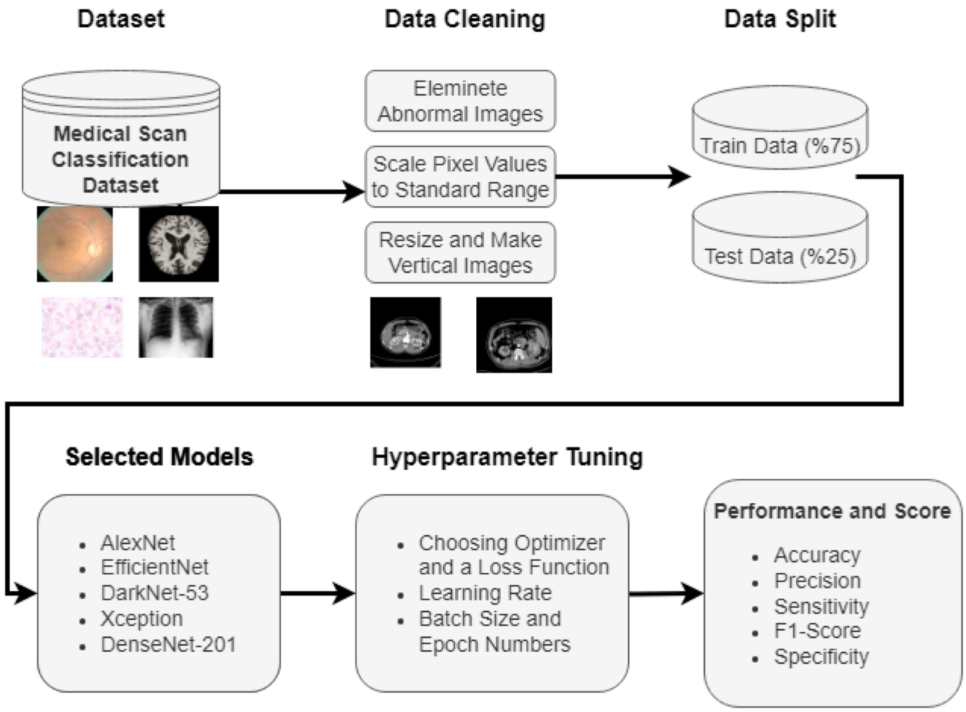

Fig. 4. Proposed System Flow Chart.

model sees the entire dataset, balancing between underfitting and overfitting. Careful tuning of these hyperparameters can dramatically improve a model's accuracy, efficiency, and generalization capabilities.

Results

The performance metrics of the network models used in the study against the learning rate are given in the Table 2.

As seen in the Table 2 above, the DenseNet-201 network gave the highest performance. When the learning rate, one of the most important parameters affecting the network performance, was changed, different model Xception network gave higher results. While the effect of the learning rate on Alexnet is 0.001, it shows 50 % performance; When training is performed with a rate of 0.0001, the performance has increased up to 98 %. Confusion matrices were used to obtain metrics. The confusion matrices of the selected deep learning networks are given below in Fig. 5, 6, 7, 8, 9, 10 and 11.

According to all these analyses, it was determined that the best performance was obtained when the DenseNet-201 learning rate was shown as 0.0001. Apart from DenseNet-201 network, Xception LR= 0.001 and EfficientNet LR= 0.0001 networks can also be used in decision support mechanisms by making improvements. When the confusion matrices of these networks are examined, it is very important for decision support systems that the margin of error usually occurs in healthy individuals while detecting tumour images very accurately.

Benchmarking

The comparison table of the proposed method and other kidney cancer detection systems are shown in Table 3.

In the context of kidney cancer detection, deep learning techniques have shown varying degrees of success across different studies [41]. On public datasets, researchers like Türk et al. [40] employed a hybrid V-Net-based model, yielding an accuracy of 97.7 % with 210 CT images, while Ma et al. [39] proposed a Heterogeneous Modified Artificial Neural Network (HMANN) and achieved an accuracy of 97.5 % with 400 CT scans.

In comparison, our proposed method utilizing the DenseNet-201 architecture significantly outperformed these models, achieving an accuracy of 99.75 % on a much larger public dataset consisting of 10,000 CT images. This improvement is attributed to the extensive dataset size, effective preprocessing steps, and hyperparameter optimization, making it one of the most reliable systems for kidney tumor detection to date. The results suggest that our model not only generalizes well to unseen data but also sets a new benchmark in terms of accuracy, making it a strong candidate for integration into clinical decision support systems.

Table 2
Score of the deployed models.

Deep Learning Model	Learning Rate	Accuracy	Precision	Sensitivity	F1-Score	Specificity
AlexNet	0.001	0.5078	0.25	0.50	0.50	.050
EfficientNet-b0	0.001	0.9550	0.9581	0.9557	0.9550	0.9557
DarkNet-53	0.001	0.7820	0.8465	0.7854	0.7727	0.7854
DenseNet-201	0.001	0.9750	0.9758	0.9754	0.9750	0.9754
Xception	**0.001**	**0.9950**	**0.9950**	**0.9951**	**0.9950**	**0.9951**
AlexNet	0.0001	0.9813	0.9813	0.9814	0.9813	0.9814
EfficientNet-b0	0.0001	0.9582	0.9608	0.9588	0.9581	0.9608
DarkNet-53	0.0001	0.9663	0.9675	0.9667	0.9663	0.9667
DenseNet-201	**0.0001**	**0.9975**	**0.9975**	**0.9975**	**0.9975**	**0.9975**
Xception	0.0001	0.9794	0.9799	0.9797	0.9794	0.9797

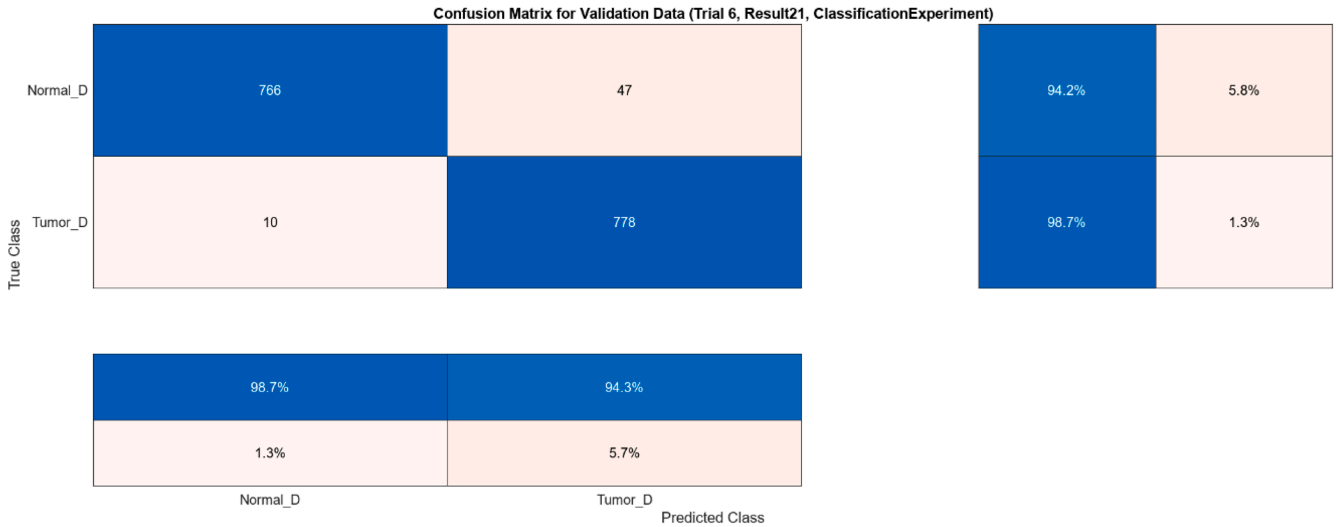

Fig. 5. Confusion matrice of AlexNet LR: 0,0001.

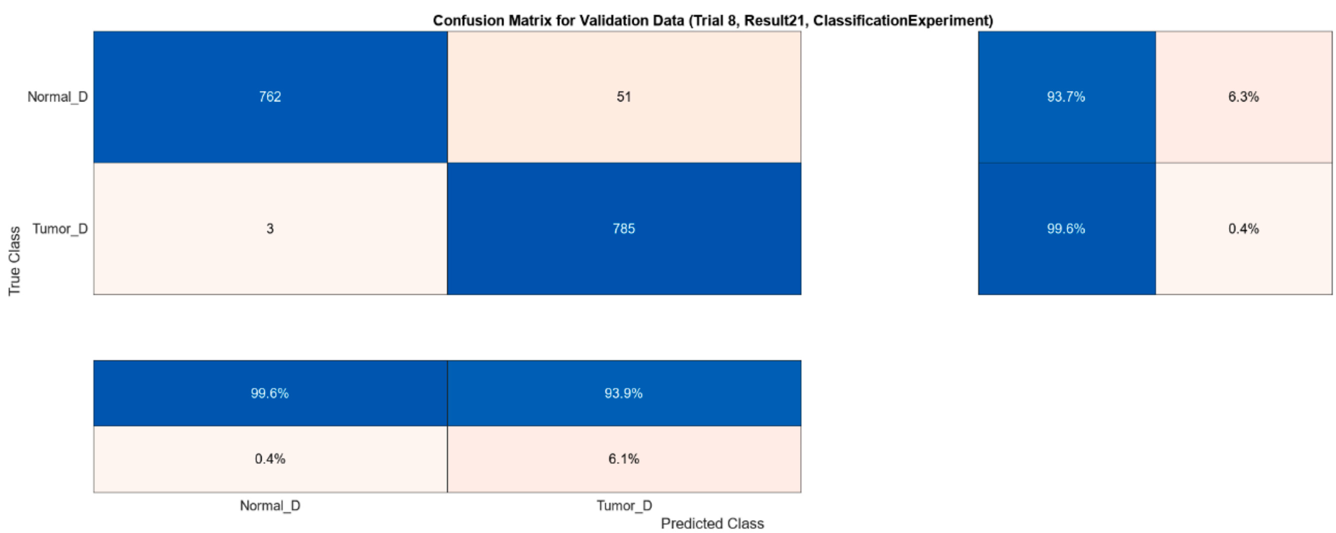

Fig. 6. Confusion matrice of DarkNet-53 LR: 0,0001.

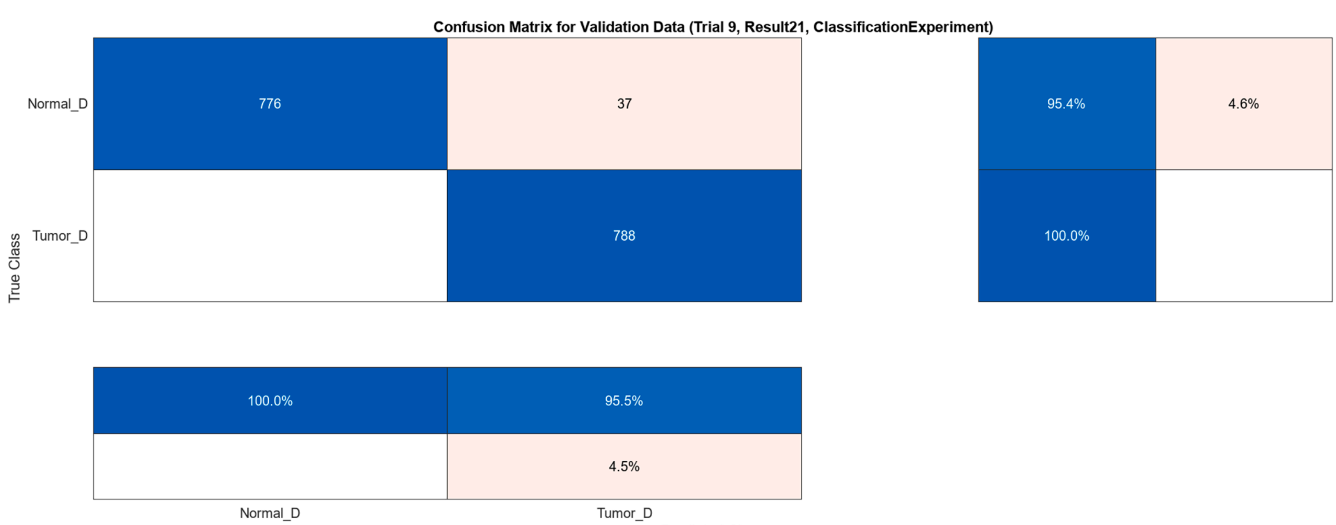

Fig. 7. Confusion matrice of DenseNet-201 LR: 0,0001.

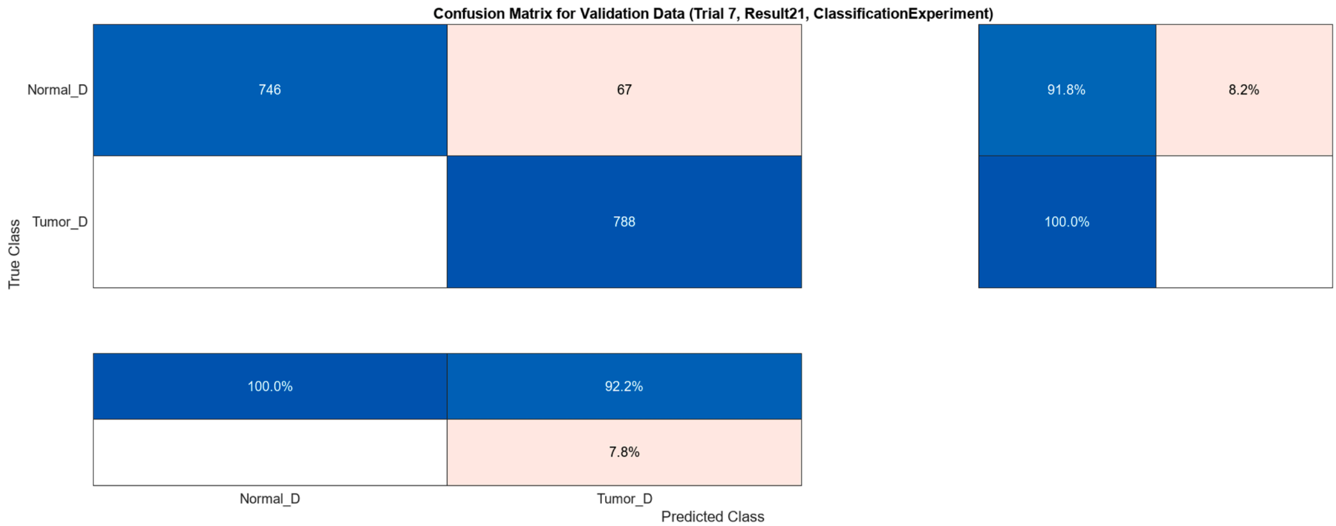

Fig. 8. Confusion matrice of EfficientNet LR: 0,0001.

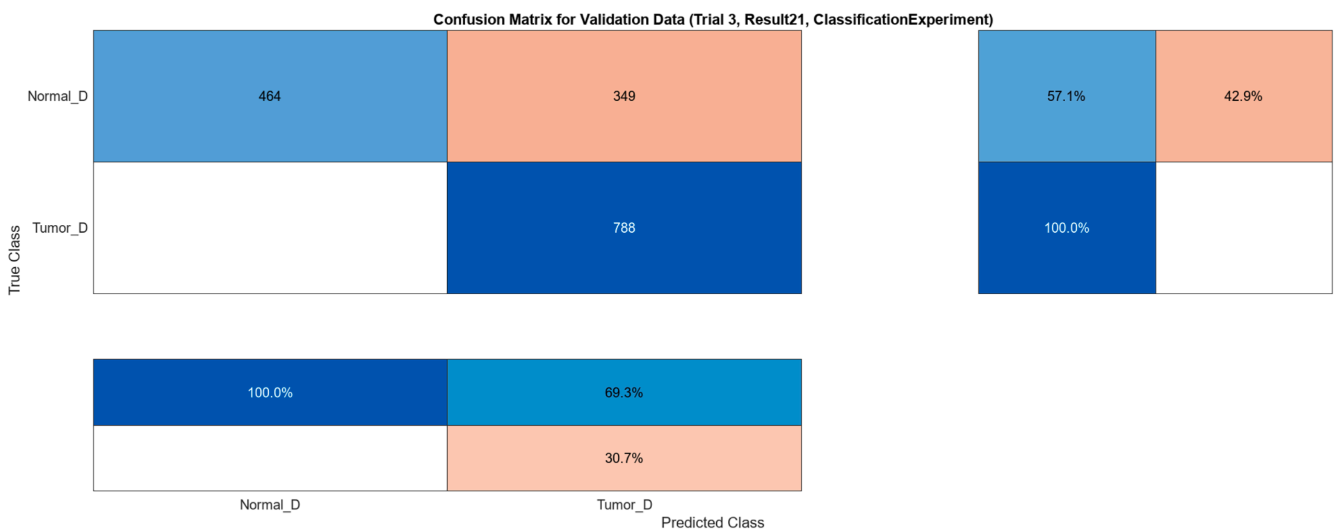

Fig. 9. Confusion matrice of DarkNet-53 LR: 0,001.

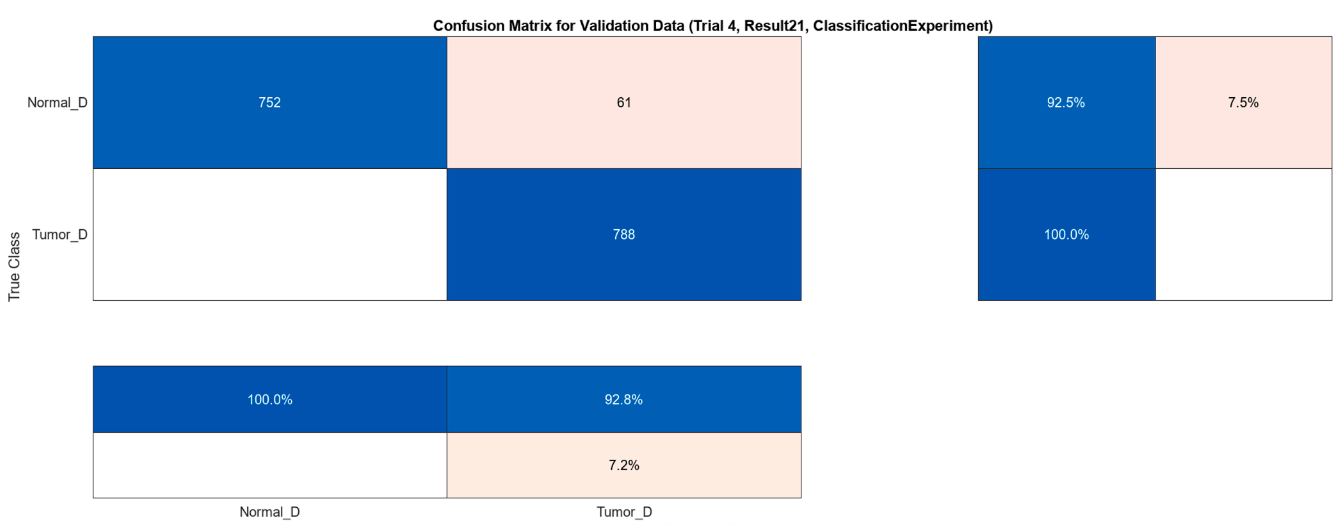

Fig. 10. Confusion matrice of DenseNet-201 LR: 0,001.

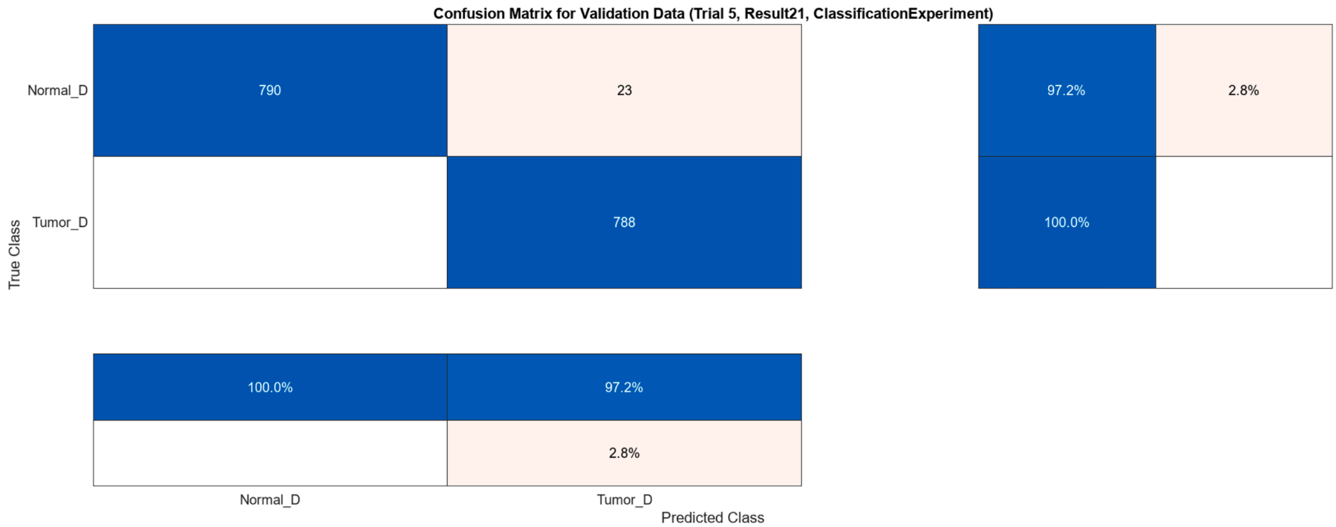

Fig. 11. Confusion matrice of Xception LR: 0,001.

Table 3
Scores of the deployed models.

Ref.	Model	Dataset	Data Size	Accuracy
[23]	LACPANet	Private	183 CT	0.9426
[27]	SVM	Private	100 CT	0.9200
[35]	YOLO	Private	300 CT	0.9320
[36]	2D CNN	Public	8400 CT	0.9200
[37]	AdaBoost, RF	Public	735 CT	0.7500
[38]	XGBoost	Public	177 CT	0.7700
[39]	HMANN	Public	400 CT	0.9750
[40]	V-Net	Public	210 CT	0.9770
This Work	DenseNet-201	Public	10,000 CT	0.9975

Conclusions

The importance of early and rapid diagnosis of serious diseases such as cancer is increasing day by day. At this point, although artificial intelligence systems are not yet in a position to take over completely, they offer great support to users even as a decision support system. In this study, a deep learning-based prediction system has been developed for kidney cancer. As can be seen in Table 3, the highest success was obtained in the comparison of the studies. The improvement of the accuracy was achieved as a result of the data engineering done on the dataset and by optimising the hyper-parameters of the deep learning networks.

For future studies, it is planned to realise a system in which deep learning networks supported by larger datasets make fully automatic decisions with high success. Also, feature extraction methods can be applied to achieve the best results for the predictive system.

Consent for publication

Not Applicable.

CRediT authorship contribution statement

Taha ETEM: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis. **Mustafa TEKE:** Validation, Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Ethics approval and consent to participate

Not Applicable.

Acknowledgements

Not Applicable.

Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Data availability

The data analyzed in this study can be downloaded from the following sites: https://www.kaggle.com/datasets/arjunbasandrai/medical-scan-classification-dataset.

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