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Enhancing Hydatid Cyst Classification with Deep Learning and Convolutional Neural Networks Using CT Scans

Mohammad Nazir Akbari[1*], Abed Azizi[1]

1. Department of Information Systems, Faculty of Computer Science, Kabul University, Kabul, Afghanistan.

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*Corresponding Author:
Mohammad Nazir Akbari
Address: Department of Information Systems, Faculty of Computer Science, Kabul University, Kabul, Afghanistan

nazirakbari28@gmail.com

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ABSTRACT

Background: Hydatid cysts, caused by *Echinococcus granulosis*, are a serious health concern with potential complications. Traditional diagnostic methods, like clinical examination and imaging interpretation, can be subjective and error-prone. Artificial Intelligence and Deep Learning techniques can revolutionize healthcare by enhancing disease detection and diagnosis, with the study focusing on precise detection and classification.

Methods: A Convolutional Neural Network (CNN) model was developed, utilizing image preprocessing techniques to accurately classify hydatid cysts in Computed Tomography (CT) scans. Training relied on a curated dataset, enabling the model to learn and identify key patterns indicative of hydatid cyst presence and its stage detection in CT scan images.

Result: The AI model employed in this study achieved a 90% accuracy in classifying hydatid cyst stages using CT scan images. By providing essential information about the cyst stage, healthcare professionals can accurately inform patients based on CT scan analysis.

Conclusion: The study explores the use of AI and DL in hydatid cyst stage classification using a CNN model trained on CT scan images. The approach aims to reduce hydatid cyst growth rates by aiding in early detection, highlighting the significant transformation in the healthcare industry due to advancements in disease detection, diagnosis, and treatment.

Kewwors: Artificial Intelligence, Deep learning, CT scan, Hydatid Cysts, CNN, Neural Networks

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1. Introduction

Hydatid cysts, caused by the parasitic infection of *Echinococcus granulosis*, present a global health challenge, requiring accurate classification and timely treatment recommendations (1). In recent years, convolutional neural networks (CNNs) have demonstrated remarkable success in medical image analysis, offering promising potential for hydatid cyst classification and treatment recommendation using CT scans (2). Accurate classification of hydatid cysts is a complex task due to their varied appearance and intricate nature (3). Traditional diagnostic methods heavily rely on human expertise, leading to time-consuming and subjective interpretations (4). To address these limitations, our study proposes a robust and automated CNN-based approach, aiming to assist healthcare professionals in making accurate and efficient diagnostic decisions.

The classification system for hydatid disease, introduced by the World Health Organization (WHO) in 2002, categorizes the parasite's viability and disease activity; this classification distinguishes between active, inactive, and transitional stages of the parasite (5). A convolutional neural network (CNN) is a powerful algorithm used in the field of artificial intelligence (AI), specifically within the domain of deep learning (DL), which is a subset of machine learning (ML) (6). A computed tomography (CT) scan is a medical imaging technique that combines X-ray images taken from different angles to create detailed cross-sectional images of the inside of the body. It provides a 3D representation of the scanned area, allowing healthcare professionals to visualize and analyze internal structures, organs, and tissues with greater clarity (7). Our approach involves training a CNN model on a large dataset of CT scans containing hydatid cyst images. The model learns to extract meaningful features from the CT scan images, enabling effective discrimination between different stages of hydatid cysts. The advantages of our approach are twofold. Firstly, it delivers precise and consistent classification results, reducing reliance on subjective interpretations. Secondly, it supports healthcare professionals in making informed decisions, ultimately enhancing patient outcomes. Our study highlights the potential of CNN-based deep learning approaches in hydatid cyst classification. The development of accurate and automated systems holds significant promise for improving diagnosis efficiency and accuracy, ultimately leading to enhanced patient care and outcomes.

2. Material and methods

The dataset utilized in this approach comprises a total of 2416 computed tomography (CT) scan images, encompassing five distinct stages of hydatid cysts. The dataset, which is accessible via the Kaggle platform (https://www.kaggle.com/datasets/tahamu/hydatid-cyst), has been carefully curated for this study (8).

Table 1: Primary dataset information

Classes	Amount	Type	Resolution
Stage 1	251	JPG	Vary
Stage 2	541	JPG	Vary
Stage 3	444	JPG	Vary
Stage 4	442	JPG	Vary
Stage 5	738	JPG	Vary

2-1. Data preprocessing:

Data preprocessing encompasses several steps, including image resizing, dataset splitting, and data augmentation (9). Firstly, for the purpose of training an excellent model and mitigating input inconsistencies during training, the images were resized to a standardized resolution of 300x300 pixels. This resizing process yields several advantages in model training, including reduced memory consumption during training, enhanced computational efficiency, and the establishment of consistent input sizes (10).

Neural networks commonly necessitate fixed-dimensional inputs, and by resizing the images to a specific size, compatibility with the model architecture is ensured. The dataset was further partitioned into three distinct sets, namely the training set, validation set, and test set (11). This division was implemented to facilitate the development and evaluation of our proposed model, ensuring a comprehensive and reliable analysis. A proportion of 70% of the data was allocated to the training set, facilitating optimal training and ensuring the model's ability to learn and capture essential patterns effectively. The test set, comprising 20% of the data, remained independent from the training process, enabling the assessment of the model's performance on unseen data. This independent evaluation provided valuable insights into the model's generalization capabilities and its capacity to accurately classify hydatid cysts. The remaining 10% of the data formed the validation set, which played a critical role in fine-tuning the model and optimizing hyperparameters. At the end of each training epoch, this set of data contributed to refining the model's performance and making necessary adjustments. The systematic partitioning of the dataset into training, validation, and test sets facilitated the development and evaluation of our proposed model, fostering a robust and unbiased analysis.

Then, data augmentation techniques were implemented to enhance the training process in our study (12). The purpose of data augmentation is to introduce diversity into the dataset, thereby improving the model's ability to generalize and handle a wide range of real-world scenarios. By applying various transformations such as rotation, translation, scaling, and flipping to the existing images, the dataset's size was effectively increased, and variations in the appearance of the hydatid cyst images were introduced. This augmentation process played a crucial role in enabling the model to learn robust features and mitigate the risk of overfitting by exposing it to a broader range of examples. Additionally, data augmentation helped address the issue of dataset imbalance. As shown in Table 2, the dataset exhibited variations in the number of data samples for each class, indicating an imbalanced dataset. Such an imbalance can lead to poor training and biased learning from the data, resulting in the model performing well for some classes while performing poorly for classes with fewer samples. To address this challenge, data augmentation techniques were applied. As a result, our model demonstrates enhanced capabilities for accurately classifying hydatid cysts in unseen images. After performing data preprocessing operations, all images were resized to a resolution of 300x300 pixels. By implementing data augmentation techniques, the dataset was expanded from 2416 images to 9417 images, introducing variations in the dataset. The augmented images were subsequently saved on disk for subsequent processing.

2-2. Proposed Model

The proposed model architecture combines the pre-trained VGG16 model with additional fully connected layers to perform the final classification task (13). The base model, VGG16, is a CNN pre-trained on the ImageNet dataset (14). During training, we freeze the base model's layers to retain pre-trained knowledge. Our architecture adds flattening and dense layers for feature extraction and non-linearity (15). Batch normalization layers stabilize training, and dropout layers prevent overfitting (16, 17). The last dense layer outputs class probabilities using the SoftMax activation (18). We compiled the model with the Adam optimizer, learning rate, and categorical cross-entropy loss for multi-class classification. Evaluation metrics include accuracy, precision, and recall.

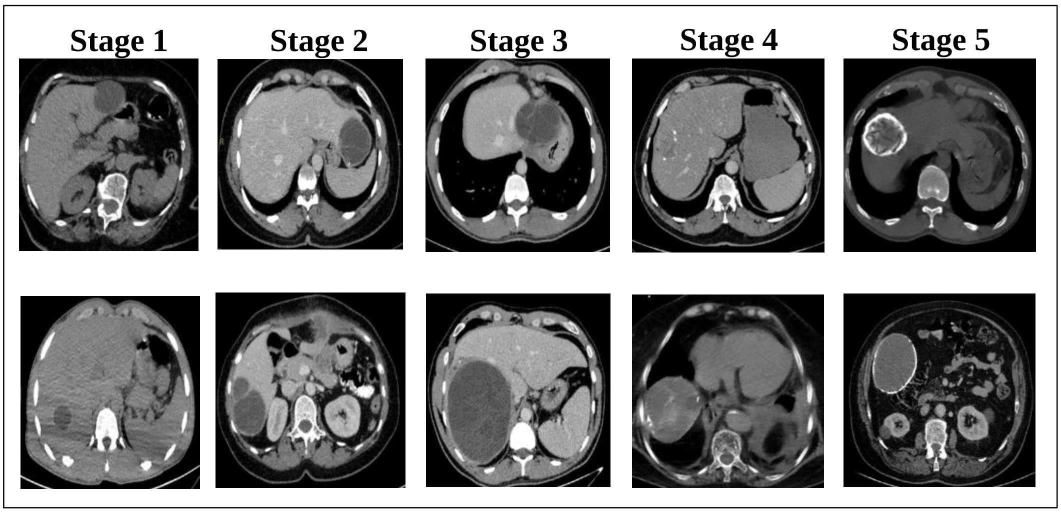

Figure 1. Hydatid cysts dataset image samples at every stage

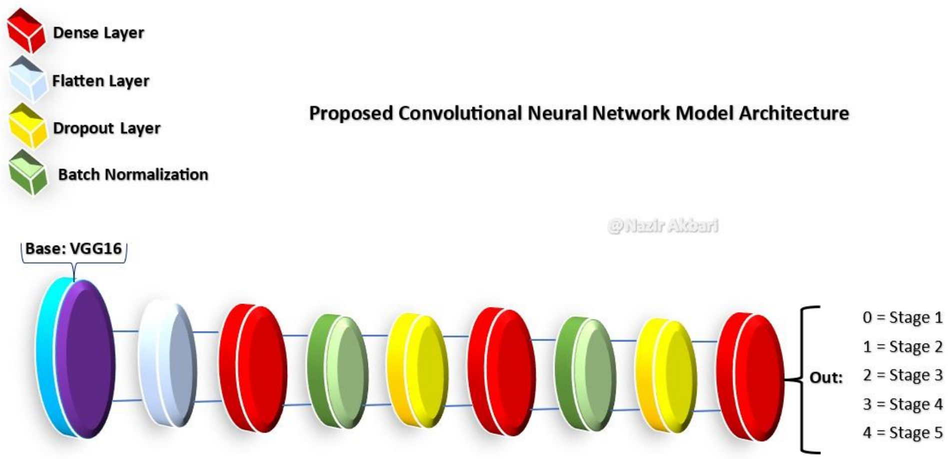

Figure 2. The CNN model architecture we created by adding the VGG16 pertained model at the top.

Base Model: The base model is VGG16, a pre-trained convolutional neural network (CNN) model that is loaded without the top layers (13). This model has been trained on the ImageNet dataset for image classification (14).

Freezing Layers: The layers of the base model are frozen, which means they are not trainable during the training process (19). This allows us to keep the pre-trained weights intact and prevent them from being updated.

Model Architecture: On top of the base model, new layers are added to create the final architecture. The additional layers are as follows:

Flatten Layer: Converts the output of the base model into a 1-dimensional feature vector (15).

Dense Layer (512 units): A fully connected layer with 512 units and a ReLU activation function, which introduces non-linearity to the model.

Batch Normalization Layer: Normalizes the activations of the previous layer, helping with training stability and accelerating convergence.

Dropout Layer (0.5): A regularization technique that randomly sets a fraction of input units to 0 during training, reducing overfitting.

Dense Layer (256 units): Another fully connected layer with 256 units and a ReLU activation function.

Batch Normalization Layer: Another batch normalization layer.

Dropout Layer (0.5): Another dropout layer.

Dense Layer (5 units): The final dense layer, with 5 units, represents the number of classes in the classification task. It uses the SoftMax activation function to output the class probabilities.

Compilation: The model is compiled using the Adam optimizer with a learning rate of 0.0001. The loss function used is categorical cross-entropy, suitable for multi-class classification (20). Additionally, metrics such as accuracy, precision, and recall are specified to evaluate the model's performance.

Model Performance: The model's performance was assessed through a comprehensive evaluation employing four distinct metrics: accuracy, precision, recall, and F1-score (21).

$$\text{Accurcy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TP} + \text{TN}}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

$$\text{F1 Score} = \frac{2 * (\text{Precision} * \text{Recall})}{\text{Precision} + \text{Recall}}$$

Where: TP – true positive, FP – false positive, TN – true negative, and FN – false negative.

3. Results

A CNN model was developed by utilizing VGG16 as the base model and incorporating additional layers. Proficiency was demonstrated in predicting the progression and severity of hydatid cysts in individuals. Effective discrimination between different stages of cyst development was exhibited. Moreover, an auxiliary technique was implemented, enabling treatment recommendations to be offered for impeding hydatid cyst growth in patients. The potential of deep learning in medical image analysis is showcased, with precise predictions and valuable treatment insights provided for enhanced patient care.

3-1. Model Evaluation Results

The testing set, previously unseen by the model, was subjected to evaluation in order to obtain a more precise assessment of its performance on novel and unfamiliar data. As illustrated in Figure 3, an analysis of the model's performance on the test set yielded evaluation metrics, revealing an accuracy rate of 0.90 (90%), a precision score of 0.90 (90%), a recall rate of 0.89 (89%), and an f-1 score of 0.90 (90%). Additionally, a loss of 0.25 was recorded on the test set; refer to Table 2. Accuracy serves as a measure of the ratio between correctly predicted outcomes and the total number of predictions made. A higher accuracy score signifies the model's ability to accurately classify a substantial portion of the samples. However, a comprehensive assessment of the model's effectiveness necessitates the computation of additional metrics such as precision. Precision quantifies the proportion of true positives among the total positive predictions made by the model, thereby identifying the model's competence in correctly labeling negative instances as negative. Conversely, recall measures the percentage of true positives relative to the actual positive instances present in the data, gauging the model's capability to identify all positive instances within the dataset. The F1 score, a harmonic mean of precision and recall, aids in achieving a balanced evaluation when faced with imbalanced classes. Ranging from 0 to 1, with 1 indicating optimal

Table 2: The model performance metrics on the test set.

Precision	Recall	F1 – score	Accuracy	Validation Loss
0.90	0.89	0.90	0.90	0.25

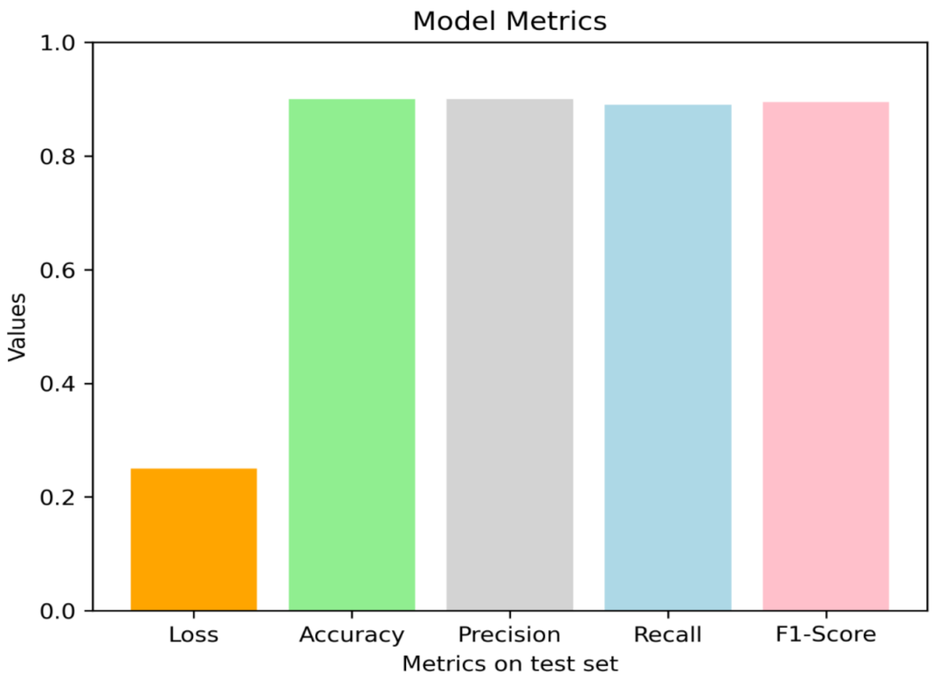

Figure 3. Showcasing the visualization of performance metrics on the test set in the form of a bar chart.

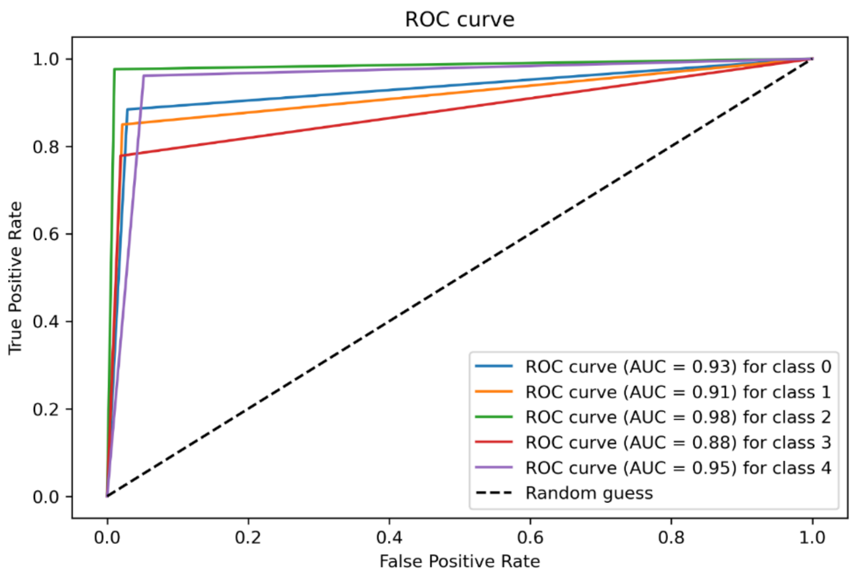

Figure 4. Visual representation of the model's performance in the form of an ROC Curve graph.

3-2. ROC Curve

The performance of a classification model is assessed through the utilization of a graph known as the Receiver Operating Characteristic (ROC) curve. In this graph, the true positive rate (TPR) is plotted against the false positive rate (FPR) at various threshold values. The separation of the signal from the noise is accomplished by this graphical representation, offering a holistic evaluation of the model's performance across all classification thresholds (22). The model's performance on the ROC curve graph is illustrated in Figure 4, revealing valuable insights into its effectiveness.

4. Discussion

A CNN-based deep learning approach was employed in our study for the classification of hydatid cysts based on CT scans. The results obtained from our comprehensive evaluation demonstrate the potential of deep learning techniques in addressing the challenges associated with accurate classification of hydatid cysts. Hydatid cysts pose a complex task for accurate classification due to their varied appearance and intricate nature. Traditional diagnostic methods heavily rely on human expertise, leading to time-consuming and subjective interpretations. Our proposed CNN-based approach overcomes these limitations by leveraging the capability of deep learning models to extract meaningful features from CT scans. By training the model on a large dataset of hydatid cyst images, precise and consistent classification results can be achieved. `The advantages of our approach are twofold. Firstly, it reduces reliance on subjective interpretations by delivering precise and consistent classification results, thereby addressing the limitations of traditional diagnostic methods. Secondly, healthcare professionals are supported in making informed decisions, leading to enhanced patient care. The dataset used in our study, comprising 2416 CT scan images of hydatid cysts, was carefully curated and augmented to introduce diversity and address the issue of dataset imbalance. Data preprocessing operations, including image resizing, dataset splitting, and data augmentation, were performed to ensure consistent input sizes, facilitate model training, and enhance generalization capabilities. The proposed model architecture combines a pre-trained VGG16 model with additional fully connected layers for feature extraction and non-linearity. By freezing the layers of the pre-trained base model, its knowledge is retained, and overfitting during training is prevented. The model's performance was evaluated using metrics such as accuracy, precision, recall, and F1-score, providing a comprehensive assessment of its effectiveness. Excellent performance was demonstrated by our model on the testing set, achieving an accuracy rate of 90%, a precision score of 90%, a recall rate of 89%, and an F1 score of 90%. These results indicate the model's ability to accurately classify hydatid cysts and make reliable predictions on unseen data. The potential of CNN-based deep learning approaches in hydatid cyst classification and treatment recommendation using CT scans was highlighted in our study. The combination of accurate classification and treatment insights offered by our approach can significantly contribute to the field of medical image analysis and ultimately improve patient care and outcomes in the management of hydatid cysts.

5. Conclusion:

The development of AI and ML has revolutionized healthcare, particularly in disease detection, diagnosis, and personalized treatment plans. Our study focused on using a CNN model to accurately classify hydatid cysts in CT scans. By training the model on a large dataset, we achieved high accuracy, precision, recall, and F1-score. This AI-based approach offers objective and consistent results, improving efficiency and supporting informed treatment decisions. Early and accurate detection of hydatid cysts improves patient care and outcomes. Future research can refine the approach by integrating additional imaging modalities and expanding the dataset for better generalizability. In conclusion, AI and ML techniques, specifically CNN-based models, enhance the diagnosis of hydatid cysts, leading to improved disease detection, treatment planning, and patient care.

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