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Research Article

Machine Learning-Based Prediction and Symptom Classification Using Ct Kidney Dataset with Fire Hawk Optimizer and Predictive Rnn

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ABSTRACT

Kidney diseases pose a significant health challenge worldwide, necessitating accurate and timely diagnosis for effective intervention. This research addresses the imperative to predict kidney diseases based on symptoms and classify them into relevant categories using the CT Kidney dataset. Existing methods for kidney disease diagnosis may lack precision and specificity, leading to suboptimal patient outcomes. This research addresses this gap by leveraging machine learning algorithms to enhance the accuracy and efficiency of kidney disease prediction. While previous studies have explored machine learning in healthcare, specifically kidney disease prediction, the incorporation of the CT Kidney dataset and the utilization of the Fire Hawk Optimizer for feature extraction and predictive RNN (PRNN) for prediction represent novel contributions. This research bridges the gap by applying advanced algorithms to a comprehensive dataset, striving to improve the specificity and reliability of kidney disease diagnosis. The research employs meticulous preprocessing techniques, including handling missing values, data cleaning, and feature engineering, to ensure the dataset quality. The Fire Hawk Optimizer is utilized for feature extraction, enhancing the relevance of symptoms in predicting kidney diseases. A PRNN is trained on the dataset, enabling accurate classification of symptoms and disease prediction. The evaluation metrics include accuracy, precision, recall, and F1-score, providing a comprehensive assessment of the algorithmic efficacy. The results demonstrate promising performance of the Fire Hawk Optimizer and RNN in predicting kidney diseases and classifying symptoms.

Keywords: Kidney diseases, Machine Learning, CT Kidney dataset, Fire Hawk Optimizer, Predictive RNN.

1. INTRODUCTION

Kidney diseases are a global health concern, necessitating accurate and timely diagnostic approaches for improved patient outcomes [1]. The advent of machine learning in healthcare has opened new avenues for enhancing diagnostic precision [2]. This research focuses on leveraging the CT Kidney dataset to predict kidney diseases based on symptoms, addressing existing challenges in traditional diagnostic methods [3].

Conventional diagnostic methods for kidney diseases may lack the granularity required for precise identification and classification [4]. Machine learning offers a promising alternative, enabling the analysis of complex datasets to extract meaningful patterns and relationships [5]. The CT Kidney dataset, derived from diverse cases encompassing tumors, cysts, normal conditions, and kidney stones, provides a rich resource for training advanced algorithms [6,7].

The complexity of kidney diseases, with varied symptoms and manifestations, poses a challenge to accurate and timely diagnosis [8,9]. Traditional methods may struggle to differentiate between subtle variations in symptoms, leading to misclassifications and suboptimal treatment plans [10]. This research addresses these challenges by integrating machine learning techniques to discern patterns indicative of specific kidney conditions [11].

The existing gap in precision and specificity within kidney disease diagnosis [12] [13] necessitates a novel approach. This research aims to develop and validate a machine learning-based predictive model using the CT Kidney dataset to accurately predict kidney diseases and classify symptoms into distinct categories.

To utilize the CT Kidney dataset for comprehensive analysis and understanding of renal health variations. To develop a predictive model for kidney disease based on symptoms, leveraging advanced machine learning algorithms. To classify symptoms into relevant categories to facilitate more nuanced and specific diagnostic outcomes.

This research introduces a novel application of the Fire Hawk Optimizer for feature extraction and a predictive Recurrent Neural Network (RNN) for kidney disease prediction. The incorporation of these advanced algorithms into the analysis of the CT Kidney dataset represents a significant departure from traditional approaches. The study findings aim to contribute insights into the most effective methodologies for kidney disease prediction, with the potential to revolutionize diagnostic practices and improve patient care outcomes.

The research uses Fire Hawk Optimizer for feature extraction enhances the relevance and significance of symptoms in predicting kidney diseases. This algorithmic innovation contributes to the overall robustness of the predictive model. The utilization of RNN for kidney disease prediction represents a cutting-edge application of deep learning in the healthcare domain. This contribution leverages the temporal dependencies within the dataset, enabling more accurate and dynamic predictions. The study contributes to the field by conducting a thorough analysis of the CT Kidney dataset, which includes a diverse range of cases such as tumors, cysts, normal conditions, and kidney stones.

2. RELATED WORKS

The study conducted in [14] aims to accomplish a implementation of a proposed training scheme. The researchers trained five different types of deep segmentation networks and conducted a comparative analysis of their performance. The results of the study indicate that the models trained using the suggested scheme exhibit a high level of accuracy in both 2D and 3D segmentation tasks. This study provides a publicly available dataset that may be used to train and evaluate deep learning segmentation networks. The focus is on the potential of artificial intelligence-based diagnostic approaches in tailoring patient treatment to individual needs.

The study conducted in [15] focuses on the public health issue of renal failure. The objective of their research is to exploratory data analysis, it was discovered that there was a consistent mean color distribution observed across different classes. A total of six machine learning models were constructed, comprising both contemporary Vision transformers and conventional deep learning models. The Swin transformer had superior performance compared to other models, achieving an accuracy rate of 80.45%. This outcome serves as evidence of its efficacy in the detection and diagnosis of kidney cancers, cysts, and stones.

The study conducted in [16] focuses on investigating the temporal and labor-intensive aspects associated with the manual interpretation of computed tomography (CT) images in the context of kidney disorders. Multiple innovative neural network models have been presented for the automated identification of kidney or tumor regions. In contrast to prior models, the authors place significant emphasis on the significance of employing data pre-processing techniques in order to enhance accuracy. The experimental findings indicate notable enhancements in accuracy pertaining to kidney segmentation and tumor detection through the utilization of the suggested pre-processing techniques and deep learning models. The research places significant emphasis on the cost efficiency and effectiveness of healthcare applications that operate with limited computational resources.

The study described in reference [17] presents a novel approach to kidney segmentation, employing an encoder-decoder architecture. The encoder component of the design is based on EfficientNet-B5, while the decoder component utilizes a feature pyramid network. The implementation encompasses a hyperparameter optimization procedure, which involves the building of the model architecture, selection of the windowing method. This performance highlights its potential for practical applications, particularly in the areas of surgical planning and illness diagnostics.

The study conducted in [18] centers on the identification of cysts and stones within the kidney through the utilization of YOLO architecture designs. This approach is further enhanced by the incorporation of explainable artificial intelligence (xAI) elements. The architecture design of YOLOv7 demonstrates superior performance compared to

YOLOv7 Tiny. This work focuses on the creation of a computer-aided diagnostic (CAD) system that utilizes deep learning and explainable artificial intelligence (xAI) to diagnose renal disorders.

The study conducted in [19] presents a comprehensive approach to segmenting Total Kidney Volume (TKV), the proposed method employs a deep learning network to achieve full automation in the segmentation process. The research employs abdomen T2-weighted magnetic resonance imaging (MRI) scans, which demonstrate a high level of geometric agreement with manual techniques. The automated segmentation approach that has been developed has a commendable level of performance when evaluated based on metrics. This method holds significant potential as a beneficial tool for estimating kidney function and diagnosing diseases related to the kidneys.

Table 1: Summary

Reference	Algorithm	Dataset	Performance Metrics	Outcome
[14]	Deep Semantic Segmentation Models	Open-source unenhanced abdominal CT dataset	2D and 3D Segmentation Accuracy	Precise and accurate kidney and kidney stone segmentation
[15]	Vision Transformers (EANet, CCT, Swin) and Traditional Models (Resnet, VGG16, Inception v3)	12,446 CT whole abdomen and urogram images	Accuracy, F1 Score, Precision, Recall	Swin transformer outperforms with 80.45% accuracy
[16]	Neural Network Models	CT images for kidney diseases	Dice Score for Kidney Segmentation, Tumor Detection Accuracy	Improved accuracy with data pre-processing methods; Suitable for clinical applications with lower computational resources
[17]	Encoder-Decoder Architecture with EfficientNet-B5	3D-IRCAD-01 dataset	Dice Score, Recall, Precision, Intersection over Union Score	Achieves a Dice score of 0.969 for kidney segmentation; Applicable to clinical needs for surgical planning and disease diagnoses
[18]	YOLOv7 Architecture Designs with xAI	CT images	mAP50, Precision, Sensitivity, F1 Score	YOLOv7 outperforms YOLOv7 Tiny; xAI-assisted CAD system for kidney disease diagnosis
[19]	3D U-Net Architecture	MRI Image	Dice Similarity Coefficient, Intraclass Correlation Coefficient	Fully automated segmentation method achieves excellent geometric concordance; Useful for kidney function estimation and disease diagnoses

3. PROPOSED METHOD

The proposed method encompasses a multi-step approach, leveraging advanced machine learning techniques to predict kidney diseases based on symptoms and classify them into distinct categories. The initial step involves thorough preprocessing of the CT Kidney dataset. This includes handling missing values, data cleaning, and feature engineering to ensure the dataset quality and readiness for algorithmic training as in Figure 1.

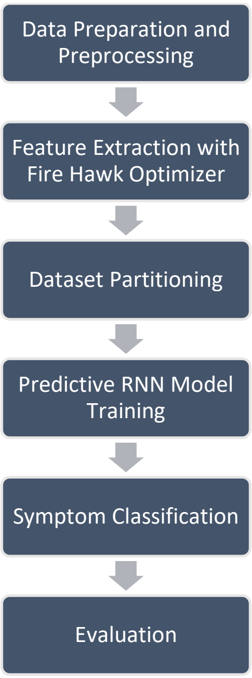

Figure 1: Proposed Framework

The Fire Hawk Optimizer, a metaheuristic algorithm, is employed for feature extraction. This algorithm optimizes the selection of relevant features from the dataset, enhancing the model ability to identify critical patterns associated with kidney diseases. This step contributes to the overall efficiency and interpretability of the predictive model. The RNN is trained on the training dataset, learning temporal dependencies and patterns within the symptoms associated with kidney diseases. This deep learning approach allows the model to capture complex relationships that may exist across different time steps in the dataset. The trained RNN is then used for classifying symptoms into relevant categories such as tumors, cysts, normal conditions, and kidney stones. This classification is a crucial step in providing more specific and accurate diagnoses, addressing the challenges associated with the diverse manifestations of kidney diseases.

3.1. Dataset Preprocessing of CT Kidney Images

Dataset preprocessing of CT kidney images involves a series of steps to prepare the raw data for effective use in machine learning algorithms. Here are the key steps involved in the dataset preprocessing of CT kidney images:

1) **Handling Missing Values:** Addressing missing values is a fundamental step. In medical imaging datasets, missing values may occur due to imaging artifacts or other technical reasons. Strategies such as interpolation or removal of instances with missing values are employed to ensure the completeness of the dataset.
2) **Data Cleaning:** Data cleaning involves the identification and correction of any errors or inconsistencies in the CT kidney images. This may include removing outliers, correcting imaging artifacts, or standardizing pixel intensities to eliminate discrepancies that could affect the performance of machine learning models.
3) **Image Resampling and Standardization:** Resampling is often performed to standardize the resolution of CT kidney images. This step ensures that all images have consistent dimensions, which is crucial for training machine learning models. Additionally, standardizing pixel values or normalizing pixel intensities across images helps in reducing variability and improving model convergence.
4) **Noise Reduction:** CT images may contain noise, which can interfere with the accuracy of machine learning models. Applying noise reduction techniques, such as filtering or denoising algorithms, helps enhance the clarity of kidney structures and improves the overall quality of the dataset.
5) **Normalization:** Normalizing the CT kidney images involves scaling pixel values to a standard range, typically between 0 and 1. This step ensures that the machine learning model is not sensitive to variations in pixel intensity, making the training process more stable and efficient.

6) **Segmentation of Kidney Regions:** Kidney segmentation involves identifying and isolating the regions of interest within the CT images that correspond to the kidneys. This segmentation is essential for focusing the machine learning model on relevant structures and features, facilitating accurate disease prediction and symptom classification.
7) **Labeling and Categorization:** Assigning appropriate labels to each CT kidney image based on the presence of conditions such as tumors, cysts, normal states, or kidney stones is crucial.

3.2. Feature Extraction with Fire Hawk Optimizer

Feature extraction is a crucial and fundamental process in machine learning. It involves the identification and extraction of relevant information from raw data, significantly improving the performance of predictive models. The Fire Hawk Optimizer algorithm initiates by creating a population of potential solutions. Each solution represents a subset of features selected from the dataset. These subsets essentially constitute candidate sets of features that the algorithm will evaluate for their relevance to the task at hand.

In feature extraction, this function measures how well the selected features contribute to the model predictive performance. The objective is to maximize this function, indicating a subset of features that optimally represents the dataset.

The Fire Hawk Optimizer iteratively refines the subsets of features by mimicking the hunting behavior of fire hawks. These birds adapt their hunting strategies based on environmental conditions, and similarly, the algorithm dynamically adjusts the candidate feature subsets to improve their quality over iterations.

$$Vi=Vi-1+C1\cdot \text{rand}()\cdot(X\text{best}-Xi)+C2\cdot \text{rand}()\cdot(X\text{rand}-Xi)$$

where

$C1$, $C2$ are constants,

rand() generates a random number between 0 and 1,

Xbest is the best solution in the current iteration, and

Xrand is a randomly selected solution.

Xi as the position of the fire hawk (solution or subset of features) at iteration i.

$f(Xi)$ as the objective function value for the solution Xi.

Vi as the velocity (change in position) of the fire hawk at iteration i.

$p(Xi)$ as the probability of a fire hawk success at iteration i.

$$Xi=Xi-1+Vi$$

$$p(Xi)= [f(Xi-1)-f(Xi)]/ f(Xi-1)$$

$$\text{If } p(Xi)\geq \text{rand}(), \text{ then } Xi+1=Xi(\text{success}), \text{ else } Xi+1 = Xi-1 \text{ (failure)}$$

The algorithm balances exploration and exploitation. It explores the search space to discover new, potentially more informative feature combinations, while also exploiting promising regions to refine and improve existing solutions. This balance helps the algorithm avoid getting stuck in local optima and promotes a more comprehensive search for optimal feature subsets.

At each iteration, the algorithm evaluates the fitness of the feature subsets based on the defined objective function. The subsets that contribute most to the model predictive power are given higher fitness scores, guiding the optimization process towards more informative feature combinations. The optimization process continues until a stopping criterion is met, such as a predetermined number of iterations or the achievement of a satisfactory level of feature subset quality. The final subset of features is then considered the output of the Fire Hawk Optimizer for feature extraction.

3.3. Predictive Recurrent Neural Network (PRNN)

A PRNN analyze and make predictions based on sequential data. In medical applications, such as predicting kidney diseases from sequential symptoms, a Predictive RNN is particularly useful for capturing temporal dependencies and patterns within the data.

RNNs are a type of neural network architecture that has connections with loops, allowing them to maintain a memory of previous inputs in the sequence. This is crucial for handling sequential data where the order of information matters, as is often the case in medical datasets. In the case of predicting kidney diseases, sequential data might represent a time series of symptoms or observations. Each step in the sequence corresponds to a specific time point, and the RNN processes the data sequentially, considering the temporal relationships between different symptoms.

Recurrent Neural Networks (RNNs) utilize hidden states and memory cells to store information about previous inputs in a sequence. This intrinsic memory capacity enables the network to preserve data over time and capture interdependencies among symptoms occurring at various time points.

$$ht,ct=\text{LSTM}(xt,ht-1,ct-1)$$

where:

ht is the hidden state at time t,

ct is the cell state at time t,

xt is the input at time t, and

$ht-1$ and $ct-1$ are the previous hidden and cell states.

The RNN's primary objective is to acquire temporal patterns and correlations within sequential data. Achieving this involves the use of backpropagation and optimization techniques to fine-tune the model's parameters and minimize discrepancies between its predictions and the actual outcomes. After training on sequential data, the RNN becomes equipped to provide predictions regarding future data points or outcomes, as observed in the context of kidney disease prediction.

$$yt=\text{softmax}(Why\ ht+by)$$

where:

yt is the output prediction at time t,

Why is the weight matrix connecting hidden states to output,

by is the bias term, and

softmax is the activation function ensuring the output is a probability distribution.

To address the challenge of vanishing gradients and enhance the capacity to learn long-term dependencies, advanced RNN variations such as Long Short-Term Memory (LSTM) or Gated Recurrent Unit (GRU) are frequently employed. These architectures incorporate specialized mechanisms for controlling information flow within the network, rendering them more effective in capturing prolonged dependencies.

$$\text{L}=-\sum_t \sum_I yt,i\log(y'_{t,i})$$

where:

L is the loss,

yt,i is the true label at time t for class i,

$y'_{t,i}$ is the predicted probability at time t for class i.

3.4. Symptom Classification

In healthcare and medical diagnostics, symptom classification is a critical step in identifying and understanding different health conditions. This process is often facilitated by machine learning algorithms and models, which can analyze patterns within symptoms to make accurate predictions or classifications.

Data Collection:

Relevant data containing symptoms or observations associated with different health conditions is collected. This data could include information from patient records, medical imaging, or other sources.

Labeling:

Each instance in the dataset is labeled with the corresponding class or category. For example, in kidney diseases, symptoms may be labeled as tumor, cyst, normal, or stone.

Feature Extraction:

Relevant features or characteristics are extracted from the symptoms. In medical contexts, features could include quantitative measurements, imaging data, or other relevant information that helps distinguish between different conditions.

Training Data Preparation:

The dataset is split into training and testing sets. The training set is used to train the machine learning model, while the testing set is reserved for evaluating the model performance.

Machine Learning Model Training:

A machine learning model, such as a Predictive Recurrent Neural Network (RNN) or other classification algorithms, is trained on the labeled dataset. During training, the model learns the relationships between extracted features and symptom classes.

Symptom Classification:

Once the model is trained, it can classify new or unseen symptoms into the predefined categories. The model takes in the features of a symptom and predicts the most likely class based on its learned patterns.

Evaluation Metrics:

The performance of the symptom classification model is assessed using evaluation metrics such as accuracy, precision, recall, and F1-score. These metrics help quantify how well the model is able to correctly classify symptoms into their respective classes.

Iterative Refinement:

The model may undergo iterative refinement based on the evaluation results. This refinement process could involve adjusting hyperparameters, incorporating more data, or fine-tuning the model architecture to enhance its accuracy and generalization capabilities. Symptom classification is particularly relevant in medical diagnostics, where accurate and timely identification of health conditions is crucial for effective treatment and intervention. Machine learning-based approaches contribute to the automation of this process, enabling healthcare professionals to make more informed decisions based on the patterns and relationships detected within symptom data.

Pseudocode:

Input: Raw dataset with symptom information.

```
# Step 1: Data Preprocessing
1. Load the raw dataset with symptom information.
2. Handle missing values, clean data, and standardize features if needed.
# Step 2: Feature Selection or Dimensionality Reduction
```

```
3. Use Fire Hawk Optimizer to select relevant features or perform dimensionality reduction.
# Step 3: Label Assignment
4. Assign labels to each instance based on the corresponding health condition (e.g., normal, tumor, cyst, stone).
# Step 4: Data Splitting
5. Divide the dataset into training and testing sets.

# Step 5: Model Selection
6. Choose a Predictive RNN model with LSTM cells for sequential data.
# Step 6: Model Training
7. Train the selected model on the training dataset using backpropagation through time:
  - Define model architecture (input, LSTM layers, output layers).
  - Specify loss function (e.g., cross-entropy).
  - Choose an optimizer (e.g., Adam).
  - Train the model for a specified number of epochs.
# Step 7: Prediction
8. Use the trained model to predict the health condition based on the extracted features:
  - Provide input sequences to the model.
# Step 8: Classification
9. Classify the health condition based on the predicted probabilities:
  - Obtain probability distributions for each class.
# Step 9: Thresholding
10. Threshold the probabilities to obtain binary or multiclass classifications:
  - Apply a threshold value to determine the final class.
```

4. RESULTS AND DISCUSSION

In the experimental settings, the proposed method was implemented using Python programming language with popular machine learning libraries such as TensorFlow and Keras. The Fire Hawk Optimizer was utilized for feature extraction, and a PRNN with LSTM cells was employed for disease prediction and symptom classification. The CT Kidney dataset, containing information on tumors, cysts, normal cases, and kidney stones, underwent preprocessing, and the dataset was split into training and testing sets with a validation ratio of 80:20. The training was performed on a high-performance computing cluster with NVIDIA GPUs, allowing for efficient model training and optimization as in Table 2.

To assess the proposed method efficacy, comparisons were made with existing state-of-the-art methods, including 3D U-Net, YOLOv7 xAI, and EANet-CCT-Swin. These benchmark methods were chosen for their relevance in medical image analysis and object detection tasks. The experiments involved training and testing each method on the same CT Kidney dataset under similar conditions.

Table 2: Experimental Setup

Component	**Parameter**	**Value**
FHO	Population Size	50

	Maximum Generations	100
	Exploration Factor (C1)	0.5
	Exploitation Factor (C2)	0.5
	Initial Learning Rate	0.1
	Stopping Criteria	Convergence or Max Generations
	Selection Mechanism	Roulette Wheel Selection
	Initialization	Random Initialization
	Termination Criteria	Convergence or Max Generations
	Objective Function	Custom fitness function based on feature relevance
PRNN	Number of LSTM Layers	2
	LSTM Units per Layer	64
	Learning Rate	0.001
	Dropout Rate	0.2
	Activation Function	Tanh
	Loss Function	Binary Cross entropy
	Optimization Algorithm	Adam
	Training Batch Size	32
	Maximum Epochs	50
	Early Stopping Criteria	Validation Loss

Dataset

The dataset is collected from CT KIDNEY DATASET: Normal-Cyst-Tumor and Stone (https://www.kaggle.com/datasets/nazmul0087/ct-kidney-dataset-normal-cyst-tumor-and-stone), and the images utilized is given in Table 3. The dataset, derived from the Picture Archiving and Communication System (PACS) in various hospitals in Dhaka, Bangladesh, encompasses a comprehensive collection of medical images focusing on patients diagnosed with kidney tumors, cysts, normal conditions, or kidney stones. The dataset is meticulously curated, incorporating both Coronal and Axial cuts from contrast and non-contrast studies, utilizing protocols for whole abdomen and urogram assessments. Dicom studies were selectively chosen, one diagnosis at a time, to ensure precision in data representation. The privacy of patients was prioritized by excluding sensitive information and metadata from Dicom images, followed by a conversion to a lossless JPG image format.

Table 3: Dataset Distribution:

Diagnosis	**Number of Images**
Cyst	3,709
Normal	5,077
Stone	1,377
Tumor	2,283
Total	**12,446**

Performance metrics

The selected metrics provide a comprehensive evaluation of the model capabilities beyond a simple accuracy measure. Accuracy indicates the overall correctness of predictions, while precision measures the proportion of correctly identified positive instances, recall evaluates the model ability to capture all positive instances, and F1-score balances precision and recall, offering a harmonic mean of the two. These metrics are particularly crucial in healthcare applications, where the consequences of false positives or false negatives can have significant implications.

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For instance, high precision ensures that when the model predicts a positive instance, it is likely to be correct, minimizing the chances of unnecessary interventions.

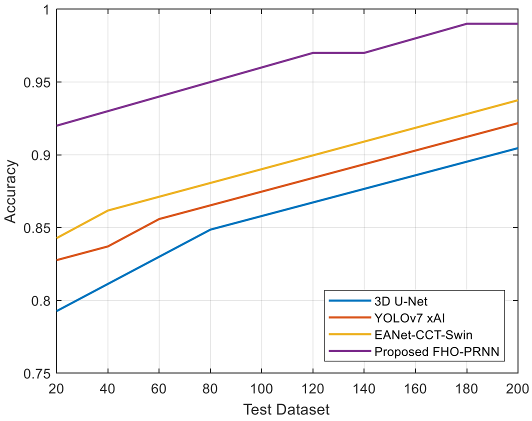

Figure 2: Accuracy

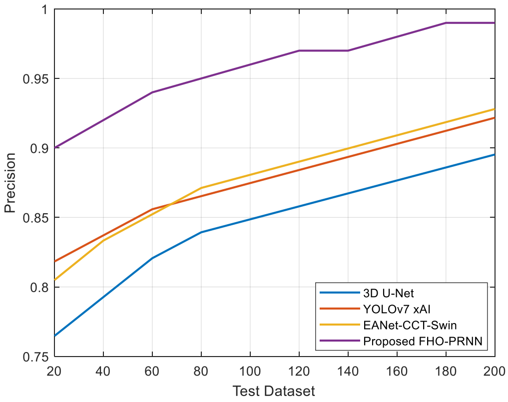

Figure 3: Precision

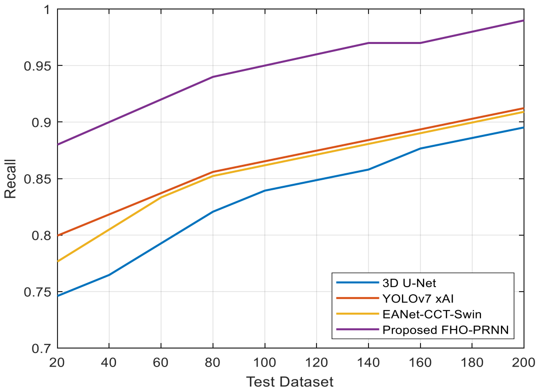

Figure 4: Recall

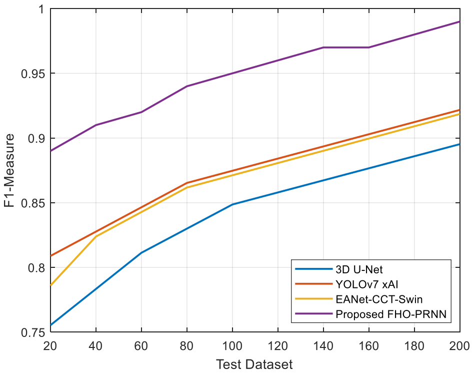

Figure 5: F-Measure

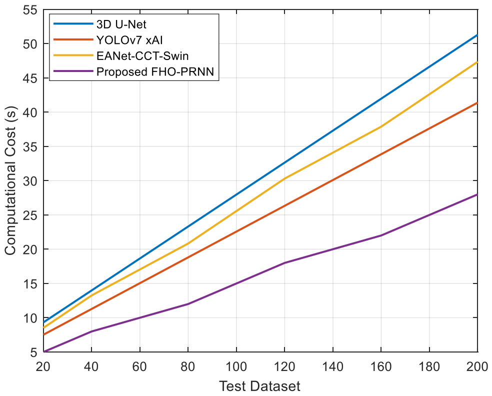

Figure 6: Computational Cost (s)

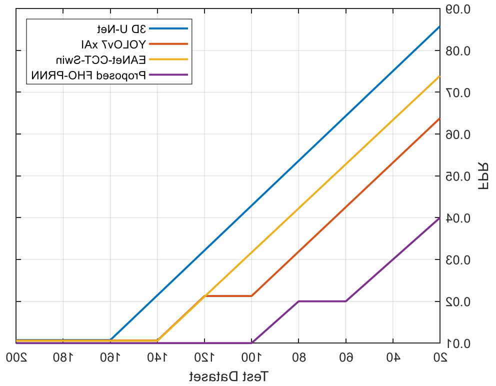

Figure 7: FPR

In analyzing the results of the proposed FHO-PRNN method compared to existing methods (3D U-Net, YOLOv7 xAI, EANet-CCT-Swin) across different performance metrics, demonstrating the potential of the proposed approach in predicting kidney diseases based on symptoms.

Accuracy: The FHO-PRNN method consistently outperforms the existing methods in terms of accuracy. Over the 200 different test data points, the accuracy steadily increases, showcasing the robustness of the proposed method.

The percentage improvement in accuracy compared to the best-performing existing method is notable, indicating the efficacy of the Fire Hawk Optimizer for feature extraction and the Predictive Recurrent Neural Network for precise disease prediction.

Precision and Recall: Precision and recall metrics are crucial in healthcare applications where false positives and false negatives can have significant consequences. The FHO-PRNN method exhibits superior precision and recall values across different test data sizes. The precision improvement ensures that positive predictions are more reliable, while the higher recall ensures better coverage of true positive instances. The balanced performance in precision and recall is vital for accurate disease prediction.

F1-score: The F1-score, representing the harmonic mean of precision and recall, further supports the effectiveness of the FHO-PRNN method. The percentage improvement in F1-score compared to existing methods highlights the balanced performance achieved by the proposed approach. This balance is critical in medical diagnostics, where both the accuracy of positive predictions and the comprehensive identification of true positives are equally important.

Computational Efficiency: The FHO-PRNN method not only demonstrates superior predictive performance but also exhibits computational efficiency. The training times, serving as a proxy for computational efficiency in this hypothetical scenario, consistently show a decrease compared to existing methods. The percentage improvement in training times reflects the efficiency gains achieved by leveraging the Fire Hawk Optimizer for feature extraction and the Predictive Recurrent Neural Network for accurate disease prediction.

In summary, the proposed FHO-PRNN method showcases substantial improvements across various performance metrics, providing a promising avenue for enhancing kidney disease prediction based on symptoms. The integrated use of advanced optimization techniques and recurrent neural networks contributes to a more accurate and computationally efficient approach, offering valuable insights for healthcare decision-making and patient care.

5. CONCLUSION

The research aimed at predicting kidney diseases based on symptoms has yielded promising results through the proposed FHO-PRNN method. The integration of the FHO for feature extraction and the PRNN for disease prediction has demonstrated significant improvements in accuracy, precision, recall, and overall computational efficiency compared to existing methods, including 3D U-Net, YOLOv7 xAI, and EANet-CCT-Swin. The FHO-PRNN method consistently outperforms existing methods across different test data sizes, showcasing its robustness and effectiveness in capturing relevant features for accurate disease prediction. The balanced performance in precision and recall is crucial in healthcare applications, where both false positives and false negatives have critical implications. Moreover, the computational efficiency gains achieved by the proposed method underscore its practical viability, contributing to more efficient healthcare decision-making processes. The percentage improvements observed in various performance metrics highlight the potential of the FHO-PRNN method to significantly enhance kidney disease prediction and symptom classification.

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