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AI-Driven Precision: Integrating Multiscale Transformer Fusion Network and Bio-Inspired Optimization for CKD Classification

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This research paper presents an innovative approach to Chronic Kidney Disease (CKD) classification by optimizing a Multiscale Transformer Fusion Network (MS-TFN) using Electric Eel Foraging Optimization (EEFO). A dataset of 1000 instances with 25 features, including patient demographics and health indicators, was preprocessed using categorical encoding and numerical normalization before being split into training and test sets. The MS-TFN integrates transformer blocks for capturing long-range dependencies with depthwise separable convolutional blocks for efficient local feature extraction, allowing for the creation of robust data representations that are processed through dense layers for accurate classification. The EEFO, a bio-inspired optimization algorithm, fine-tunes the learning rate and batch size by balancing exploration and exploitation. This synergy achieved a classification accuracy of 99.9%, demonstrating significant potential for clinical application. However, the study's limitation lies in the generalizability of the results, as the dataset is limited in size and population scope, requiring further validation with more diverse datasets. This work introduces a novel combination of transformer and convolutional blocks in the MS-TFN architecture alongside bio-inspired EEFO, offering a promising tool for early CKD diagnosis and personalized treatment plans in clinical settings.

Keywords: Chronic Kidney Disease (CKD), Multiscale Transformer Fusion Network (MS-TFN), Electric Eel Foraging Optimization (EEFO), Medical Data Classification, Hyper parameter Optimization.

1. Introduction

Chronic Kidney Disease (CKD) constitutes a major global health concern, impacting over 10% of the population and leading to millions of deaths annually due to the lack of accessible treatment alternatives. The 2020 worldwide Burden of Disease survey indicated that Chronic Kidney Disease (CKD) was the 27th leading cause of worldwide mortality in 1990. Nevertheless, it reached the 18th rank in 2010, indicating significant increase comparable to that of HIV and AIDS . Currently, around 2 million individuals globally are undergoing dialysis or kidney transplants to sustain their lives. This fraction may account for merely 10% of the total individuals necessitating such therapy. Treatment for renal failure predominantly occurs in five countries: the United States, Japan, Germany, Brazil, and Italy, which collectively account for merely 12% of the global population. In contrast, merely 20% of those undergoing treatment live in over 100 impoverished nations, which collectively encompass more than half of the global population . More than 80% of patients receiving treatment for renal failure reside in prosperous nations with universal healthcare and a significant senior demographic.

The prevalence of chronic kidney disease (CKD) is projected to rise disproportionately in developing nations like China and India, attributed to the increasing elderly population in these regions. The cost of dialysis or kidney transplantation is a significant financial strain for many individuals in middle-income nations who require these procedures. In 112 more countries, a significant proportion of the population cannot afford medical care, leading to the unfortunate demise of approximately 1 million individuals each year owing to untreated renal failure. The annual cost of controlling Chronic Kidney Disease (CKD) in the United States is anticipated to surpass $48 billion. Treatment for renal failure accounts for 6.7% of the overall Medicare budget, but benefiting fewer than 1% of the population. China's economy is anticipated to suffer a loss of US$558 billion over the next decade as a result of the impact of heart disease and kidney ailments on mortality and disability rates. The annual cost of dialysis in Uruguay is around $23 million, accounting for 30% of the budget allocated for specialized therapies by the National Resources Fund. An analysis by NHS Kidney Care reveals that chronic kidney illness generates more costs in England than the total expenditures for breast, lung, colon, and skin malignancies combined. The projected cost for managing existing and future instances of renal failure in Australia until 2020 was calculated at $12 billion . Approximately 20% of men and 25% of women aged 65 to 74 globally are projected to have Chronic Kidney Disease (CKD) .

Non-communicable diseases, such as cardiovascular disease, diabetes, and kidney disease, have supplanted communicable diseases like influenza, malaria, and AIDS as the primary causes of premature mortality worldwide . Approximately 80% of this burden is concentrated in low- or middle-income countries, with 25% impacting persons under the age of 60 . Chronic Kidney Disease (CKD) constitutes a worldwide health crisis. In 2005, the World Health Organization reported about 58 million global fatalities, approximately 35 million of which were attributable to chronic diseases. Chronic kidney disease (CKD) is treatable by pharmacological intervention, and early detection and treatment can slow or prevent the progression of the disease. Consequently, it is imperative to render accurate and prompt diagnosis to improve patient outcomes. Traditional machine learning techniques have been employed to categorise chronic kidney disease (CKD), although recent advancements in deep learning and bio-inspired optimization algorithms offer novel opportunities for improving predicting accuracy .

This research presents a new method that integrates a Multiscale Transformer Fusion Network (MS-TFN) with Electric Eel Foraging Optimization (EEFO) to improve the categorization of Chronic Kidney Disease (CKD).

Incidence and Worldwide Impact of Chronic Kidney Disease (CKD)

Chronic Kidney Disease (CKD) affects about 10% of the global population, amounting to more than 800 million individuals. Chronic kidney disease (CKD) is particularly prevalent in older persons, females, racial minorities, and individuals with diabetes mellitus and hypertension. It presents a significant burden, especially in low- and middle-income nations, which possess constrained capacity to address its consequences. The global prevalence of chronic kidney disease (CKD) stages 1-5 is estimated at 13.4%, with a specific prevalence of 10.6% for CKD stages 3-5 .

Temporal Patterns

In 2017, the global prevalence of chronic kidney disease (CKD) was estimated at 843.6 million individuals, indicating a rising trend among those afflicted by this disorder. The mortality rate in people with end-stage kidney disease (ESKD) has decreased; nonetheless, chronic kidney disease (CKD) continues to be a major global cause of death. In many high-income nations, the prevalence of chronic kidney disease (CKD) has shown a constant or decreasing trend, despite the rising incidence of risk factors including diabetes and obesity.

Definitions and Potential Traps

In epidemiology, research is undertaken to examine the trends, causes, and consequences of diseases within communities. Chronic kidney disease (CKD) is generally diagnosed through laboratory tests, primarily by measuring the glomerular filtration rate (GFR) using markers such as serum creatinine or cystatin C. Another approach entails analysing urine for the presence of albumin or protein [22]. Numerous professional organisations have established categorisation methods to systematically diagnose and monitor Chronic Kidney Disease (CKD); however, the varying criteria may influence prevalence estimates. Research demonstrates considerable diversity in the prevalence of chronic kidney disease (CKD) based on the laboratory criteria employed and the application of International Classification of Diseases (ICD) diagnosis codes.

Effects of Patient Characteristics and Comorbidities
The criteria and mechanism of chronic kidney disease (CKD) affect its prevalence. A negative correlation occurs between advancing age and glomerular filtration rate (GFR), resulting in a higher prevalence of chronic kidney disease (CKD) among the older population. Chronic kidney disease (CKD) exhibits a higher prevalence in females compared to males, influenced by intricate underlying causes, which may encompass the possibility of overdiagnosis in women . The prevalence of chronic kidney disease (CKD) varies significantly by race, as evidenced by extensive statistics, especially in the United States. Non-Hispanic Blacks and Mexican Americans demonstrate a higher prevalence of chronic kidney disease (CKD) compared to non-Hispanic Whites . Diabetes mellitus is the primary risk factor for chronic kidney disease (CKD) in developed nations, leading to a notable rise in CKD prevalence

among diabetic individuals. A substantial link exists between hypertension and chronic kidney disease (CKD), with hypertensive patients exhibiting a greater susceptibility to CKD .

Death Rate Linked to Chronic Kidney Disease

Chronic kidney disease (CKD) significantly contributes to worldwide mortality and has shown an increase in associated death rates in recent decades. From 1990 to 2017, the global mortality rate for chronic kidney disease (CKD) increased by 41.5% across all age demographics. By 2040, Chronic Kidney Disease (CKD) is projected to be the sixth biggest cause of years of life lost globally.

2. LITERATURE REVIEW / RELATED WORKS:

Gokiladevi, M., and Sundar Santhoshkumar [1] "Henry Gas Optimization Algorithm with Deep Learning based Chronic Kidney Disease Detection and Classification Model."

Chronic Kidney Disease (CKD) is a progressive condition that can lead to kidney failure if not diagnosed early. Detecting CKD in its early stages is crucial for effective management, but traditional diagnostic methods may fail to identify the disease in its initial phases. To address this challenge, Gokiladevi and Sundar Santhoshkumar propose an automated CKD detection system using a combination of the Henry Gas Optimization Algorithm (HGSO) and Deep Learning (DL) techniques, known as CKDD-HGSODL.

The proposed approach integrates several key components to improve CKD detection. First, the authors apply min-max scaling for data normalization, ensuring that all input features are within a consistent range, thus enhancing model performance. Next, HGSO is used for feature selection, identifying the most relevant features from the dataset to reduce dimensionality and improve the efficiency of the deep learning model. The core of the detection process involves an Attention-based Gated Recurrent Unit (AGRU) model, a type of Recurrent Neural Network (RNN) that is particularly effective for sequential data and captures temporal dependencies in CKD progression.

To optimize the AGRU model, the authors use the Slime Mould Algorithm (SMA) for hyper parameter tuning. This bio-inspired algorithm fine-tunes the model’s parameters, ensuring better accuracy and robustness.

The approach is validated using a benchmark CKD dataset, with results demonstrating improved detection accuracy compared to traditional methods. The study highlights the potential of combining optimization algorithms with deep learning to create efficient, automated systems for early CKD detection, providing a valuable tool for healthcare practitioners.

Bilal, A., Alzahrani, A., Almuhaimeed, A., Khan, A. H., Ahmad, Z., & Long, H. [2] . Advanced CKD Detection through Optimized Metaheuristic Modeling in Healthcare

In healthcare informatics, effective data categorization plays a critical role in predicting and diagnosing diseases, especially Chronic Kidney Disease (CKD), which requires accurate detection for timely intervention. Traditional machine learning and deep learning models, while effective, face challenges such as high dimensionality, computational complexity, and long execution times. To address these issues, Bilal et al. propose a novel classification model that utilizes met heuristic methods to enhance CKD diagnosis.

The proposed model begins with data pre-processing, including handling missing values, data transformation, and normalization, to ensure clean and optimized input for analysis. The Binary Grey Wolf Optimization (BGWO) algorithm is then applied for feature selection. BGWO, a met heuristic method, selects the most relevant features, reducing data dimensionality and improving computational efficiency.

For classification, the study uses the Extreme Learning Machine (ELM) model, known for its fast training and high classification accuracy. The ELM model is optimized through the BGWO method, enhancing its ability to predict CKD accurately. The performance of the model is evaluated using metrics such as accuracy, recall, specificity, F-score, and kappa.

The results demonstrate that the BGWO-ELM model significantly outperforms existing CKD detection methods in terms of accuracy and efficiency. By reducing dimensionality and optimizing feature selection, the model achieves better results with lower computational costs.

Bilal et al.'s work presents an advanced solution for CKD detection, offering a more efficient and accurate method compared to traditional techniques. The integration of metaheuristic optimization with machine learning models could revolutionize disease diagnosis in healthcare, providing valuable tools for clinical decision-making.

Ismail, W. N.[3]. Snake-Efficient Feature Selection-Based Framework for Precise Early Detection of Chronic Kidney Disease. Diagnostics, 13(15), 2501.

Chronic Kidney Disease (CKD) is a progressive condition that can lead to kidney failure if not detected early. Early diagnosis is critical for improving patient outcomes and reducing the overall burden of CKD-related mortality. Manual screening of CKD, however, is time-consuming and prone to human error. To address this, many recent studies have focused on developing automated systems using machine learning (ML) techniques, which can provide more efficient and reliable early detection.

In this paper, Walaa N. Ismail introduces a novel feature selection-based framework called CKD-SO (Chronic Kidney Disease Snake Optimization), aimed at improving CKD detection accuracy. The framework employs a Snake Optimization (SO) algorithm, which mimics the behavior of snakes during hunting to find optimal or near-optimal solutions in complex problem spaces. This method is used to select the most relevant features from medical data, helping to reduce the curse of dimensionality and improve the performance of ML models.

The CKD-SO framework integrates five machine learning algorithms, and the SO algorithm is applied to optimize the feature selection process. This combination results in a highly accurate prediction model for CKD, achieving an impressive 99.7% accuracy. The optimized feature selection process ensures that only the most important variables are used for prediction, which improves model performance and efficiency.

The study highlights the effectiveness of combining nature-inspired optimization algorithms with machine learning to solve complex healthcare problems. By using the CKD-SO model, healthcare systems can achieve better early detection of CKD, enabling timely intervention and reducing the associated healthcare burden. This approach contributes to advancing automated systems for disease diagnosis and supports proactive healthcare management.

Moreno-Sánchez, P. A. [4] Data-Driven Early Diagnosis of Chronic Kidney Disease: Development and Evaluation of an Explainable AI Model.

Chronic Kidney Disease (CKD) is a growing global health issue, often leading to premature mortality if not diagnosed early. Timely diagnosis of CKD can prevent further kidney damage, reducing healthcare costs. While Artificial Intelligence (AI) and Machine Learning (ML) hold significant promise for early CKD detection, clinicians are often hesitant to adopt AI models due to the "black-box" nature of these predictions. To address this challenge, Explainable AI (XAI) has emerged as a solution to provide transparency in AI models, enabling clinicians to understand the rationale behind predictions.

In this paper, Pedro A. Moreno-Sánchez (2023) introduces an explainable AI model designed for the early diagnosis of CKD. The model is developed using an optimization framework that seeks to balance both classification accuracy and explainability. The core contribution of this study is the development of a data-driven model that quantifies the contribution of specific clinical features to CKD prediction.

The proposed model utilizes an Extreme Gradient Boosting (XGBoost) classifier, selecting three key features: hemoglobin, specific gravity, and hypertension. With an impressive 99.2% accuracy and 97.5% accuracy using 5-fold cross-validation on unseen data, the model demonstrates high predictive power. The explainability analysis reveals that hemoglobin is the most influential feature, followed by specific gravity and hypertension. The use of a small number of features not only enhances model explainability but also reduces diagnostic costs, making this approach especially promising for resource-limited settings, such as developing countries.Moreno-Sánchez's work highlights the potential of combining AI and explainability to improve healthcare outcomes, making early CKD detection more accessible and interpretable for clinical use.

Lambert, J. R., & Perumal, E. [5] Optimal Feature Selection Methods for Chronic Kidney Disease Classification using Intelligent Optimization Algorithms. Chronic Kidney Disease (CKD) classification has become an important research focus in medical data analytics, with numerous algorithms developed to predict and identify CKD early. However, the inclusion of numerous features in the classification process often increases computational complexity and reduces the effectiveness of the algorithms. To address these challenges, feature selection (FS) methods are proposed to reduce dimensionality, minimize computational complexity, and improve model performance. While several bio-inspired FS methods have been developed, there is a need to evaluate their effectiveness in the context of CKD classification.

In this paper, Lambert and Perumal propose a framework that combines multiple FS techniques to enhance CKD classification. The authors compare three popular bio-inspired FS methods: Ant Colony Optimization (ACO), Genetic Algorithm (GA), and Particle Swarm Optimization (PSO). These algorithms are employed to select the most relevant features from a CKD dataset, improving the performance of subsequent classification.

After applying the FS methods, a Logistic Regression (LR) classifier is used for the final classification task. The paper empirically tests the framework on a benchmark CKD dataset to evaluate the effectiveness of ACO, GA, and PSO in improving classification performance.

The results indicate that the ACO-FS method outperforms both GA-FS and PSO-FS, providing the best feature selection for CKD classification. By reducing the number of irrelevant or redundant features, the FS methods significantly improve classification accuracy and computational efficiency.Lambert and Perumal's study highlights the importance of FS in CKD classification and suggests that bio-inspired optimization algorithms, particularly ACO, can improve the efficiency and accuracy of medical predictions, offering a robust solution for CKD detection.

Mehta, R., Yildiz, B., Sait, S. M., & Yıldız, A. R.[6] . Optimization of Electric Vehicle Design Problems Using Improved Electric Eel Foraging Optimization Algorithm. The design and optimization of electric vehicles (EVs) present significant challenges due to the complexity and multidisciplinary nature of the problems involved, such as battery efficiency, weight reduction, and cost minimization. To address these challenges, Ranav Mehta et al. (2024) propose a novel optimization approach called the Modified Electric Eel Foraging Optimization (MEELFO) algorithm, which integrates Artificial Neural Networks (ANNs) with met heuristic methods for solving engineering design problems effectively.

The MEELFO algorithm is inspired by the foraging behaviour of electric eels, which combine exploration and exploitation techniques to find optimal food sources. The algorithm consists of four key phases: interactions, resting, hunting, and migrating. Each phase is mathematically formulated to guide the algorithm through the solution space. These phases enable the algorithm to balance between searching for new solutions (exploration) and refining existing solutions (exploitation), which enhances its ability to find optimal solutions in complex, multidimensional spaces.The MEELFO algorithm is applied to several real-world optimization problems, including the weight optimization of engineering components, economic optimization of pressure handling vessels, and cost optimization of welded beams. The authors compare the performance of MEELFO against existing Meta heuristic algorithms, demonstrating that it outperforms other methods in terms of solution quality, computational efficiency, and the ability to minimize deviations.

The results indicate that the MEELFO algorithm is particularly effective in optimizing multidisciplinary problems, including EV design, where it can be used to achieve improvements in both cost and performance. This research presents MEELFO as a promising tool for addressing complex design challenges in electric vehicle development and other engineering fields.

Lin, G., & Chen, L.[7]. A Multi-scale Fusion Network with Transformer for Medical Image Segmentation.Medical image segmentation is a critical task in healthcare for accurately identifying and delineating anatomical structures or pathological regions, often requiring the integration of complex features at different scales. In this paper, Lin and Chen introduce a novel Multi-scale Fusion Network (MSFN) that combines the strengths of Convolutional Neural Networks (CNNs) and Transformers to improve medical image segmentation. Their approach aims to exploit both local and global features effectively for better segmentation performance.

The proposed architecture incorporates a U-shaped attention model with multi-scale blocks in the encoder phase to capture multi-scale semantic information. These blocks enable the network to efficiently process features at various scales, which is essential for accurately capturing spatial details in medical images. The key innovation of the model is the cross-fusion of multi-scale channels with a Transformer, which facilitates the reconstruction of skip connections. This cross-fusion allows the decoder to access different levels of long-range contextual information, improving the quality of segmentation.

Additionally, the network employs a scale-aware pyramid fusion module at the bottom of the framework. This module dynamically fuses multi-scale contextual information, which further enhances the model's ability to handle complex patterns and structures in medical images.

The experimental results on two medical image datasets demonstrate that the proposed MSFN outperforms other comparison networks in terms of segmentation accuracy and robustness. By improving both local feature extraction and long-range contextual understanding, the proposed method reduces the computational burden on physicians and enhances the clinical application of automated image segmentation systems.

Wu, H., Huang, P., Zhang, M., Tang, W., & Yu, X. [8]. CMTFNet: CNN and Multiscale Transformer Fusion Network for Remote-Sensing Image Semantic Segmentation.Semantic segmentation of high-resolution remote-sensing images is a complex task that requires the extraction of both local and global contextual information. Traditional Convolutional Neural Networks (CNNs) excel at capturing local features but struggle with modeling long-range dependencies. On the other hand, Transformers are highly effective in capturing global contextual information through multi-head self-attention mechanisms. In this paper, Wu et al. propose a novel network architecture called CMTFNet (CNN and Multiscale Transformer Fusion Network), which combines CNNs and Transformers to address both local feature extraction and long-range dependency modeling for semantic segmentation in remote-sensing imagery.

CMTFNet utilizes an encoder-decoder structure, with a CNN-based encoder designed to extract local features from high-resolution remote-sensing images. To process these features, the authors introduce a transformer decoder that leverages a Multiscale Multihead Self-Attention (M2SA) module. The M2SA module is crucial for capturing rich multiscale global contextual information, which improves the model’s ability to understand complex image patterns. Furthermore, the transformer block incorporates an Efficient Feed-Forward Network (E-FFN) to enhance information interaction between different channels in the feature map.To fully fuse the extracted information from different levels, CMTFNet introduces a Multiscale Attention Fusion (MAF) module. This fusion mechanism ensures that both local and global contextual information are effectively combined, leading to more accurate segmentation.The performance of CMTFNet is extensively evaluated on the ISPRS Vaihingen and Potsdam datasets, with results demonstrating superior performance over existing methods in remote-sensing image segmentation. The combination of CNNs for local feature extraction and Transformers for global contextual understanding establishes CMTFNet as a powerful model for high-resolution remote-sensing image semantic segmentation.

Song, P., Li, J., An, Z.-Y., Fan, H., & Fan, L.[9]. CTMFNet: CNN and Transformer Multiscale Fusion Network for Remote Sensing Urban Scene Imagery Semantic segmentation of urban scene imagery plays a crucial role in applications such as land cover mapping, urban change detection, and environmental monitoring. Convolutional Neural Networks (CNNs) have been dominant in these tasks due to their ability to hierarchically represent local feature information.

However, CNNs face limitations in capturing global contextual information, which is essential for understanding complex urban scenes. The transformer architecture, with its ability to model long-range dependencies, has emerged as a promising solution for global context extraction, but it struggles with capturing local details. To address these challenges, Song et al. Propose a novel CNN and Transformer Multiscale Fusion Network (CTMFNet), designed specifically for the semantic segmentation of urban scene imagery. CTMFNet utilizes an encoding-decoding structure that combines CNNs for local feature extraction and transformers for global context modeling. To effectively fuse local and global information, the authors introduce a Dual Backbone Attention Fusion Module (DAFM). This module couples the local and global context information from the dual-branch encoder, enhancing the overall segmentation accuracy. Additionally, to bridge the semantic gap between different scales, the authors propose a Multi-layer Dense Connectivity Network (MDCN) as the decoder. The MDCN facilitates the seamless flow of semantic information between scales, using upsampling and residual connections to ensure that features from multiple scales are effectively fused. The proposed method is evaluated through extensive subjective, objective, and ablation experiments on the ISPRS Vaihingen and Potsdam datasets, where it outperforms existing methods in terms of segmentation accuracy. The integration of CNNs and transformers in CTMFNet effectively combines local detail extraction and global context understanding, making it a powerful model for remote sensing urban scene segmentation.

Vibashan, V. S., Valanarasu, J. M. J., Oza, P., & Patel, V. M. [10]. Image Fusion Transformer.Image fusion is a technique used to combine images from different sensors to create a single, enhanced image that contains more informative features. Traditional fusion methods, particularly those based on Convolutional Neural Networks (CNNs), focus on extracting local features to combine them. While CNN-based approaches have demonstrated effectiveness in fusing images, they often fall short when it comes to capturing long-range dependencies and global contextual information. This limitation is particularly critical in tasks that require understanding the broader structure of the image. In this paper, Vibashan et al. propose a novel Image Fusion Transformer (IFT) to address this gap by leveraging the capabilities of transformer models, which are specifically designed to model long-range dependencies through self-attention mechanisms.

The IFT model consists of a two-stage training approach. In the first stage, an auto-encoder is used to extract deep features from the input images at multiple scales. This allows the model to capture both fine details and broader contextual information from the images. In the second stage, a Spatio-Transformer (ST) fusion strategy is employed to fuse the multi-scale features. The ST fusion block is composed of two branches: a CNN branch that captures local features and a transformer branch that captures global contextual information. This multi-scale, hybrid fusion mechanism enables the model to effectively attend to both local and long-range features, thereby enhancing the quality of the fused image.

Extensive experiments on benchmark datasets demonstrate that the proposed IFT outperforms several competitive image fusion algorithms, achieving better performance in terms of both visual quality and feature preservation. Additionally, an ablation study highlights the effectiveness of the proposed ST fusion strategy in improving fusion accuracy.

The categorization of Chronic Kidney Disease (CKD) is a crucial study domain (EEFO).The categorization of Chronic Kidney Disease (CKD) is a crucial study domain owing to its substantial consequences for timely diagnosis and therapeutic management. Multiple research initiatives have investigated the utilization of machine learning and deep learning methodologies to improve the accuracy of Chronic Kidney Disease (CKD) classification. Additionally, bio-inspired optimization methodologies have been widely employed to enhance model performance. This section provides a summary of current research on the classification of Chronic Kidney Disease (CKD), deep learning models, and biologically-inspired optimization methods. It underscores the shortcomings of current methodologies and the potential advantages of amalgamating the Multiscale Transformer Fusion Network (MS-TFN) with Electric Eel Foraging Optimization (EEFO).

CKD Classification

The classification of chronic kidney disease (CKD) involves categorising individuals based on the various stages of renal impairment, often by the analysis of clinical and laboratory data. Traditional methodologies relied on statistical techniques and simpler machine learning models. Decision Trees, Support Vector Machines (SVM), and Random Forests have been employed to assess CKD datasets, producing varying degrees of efficacy [11], [12]. Nonetheless, these strategies often face challenges when addressing data characterised by high dimensionality and complex patterns common in medical datasets.

Convolutional Neural Networks (CNNs): Especially adept at processing image data, they have been effectively utilised in numerous medical imaging applications, including CKD classification [31]. Their efficacy is rooted in their capacity to encapsulate spatial hierarchies within images through the utilisation of convolutional layers, pooling layers, and fully linked layers. Notwithstanding their efficacy, CNNs frequently require considerable amounts of labelled data and are prone to overfitting [13].

Long Short-Term Memory (LSTM) [14] Networks: A specialised type of Recurrent Neural Network (RNN) engineered to recognise and comprehend patterns in temporal sequential input. Time-series data in chronic kidney disease categorisation, including patient history and renal function progression, have undergone analysis [15]. LSTMs mitigate the vanishing gradient problem prevalent in standard RNNs, rendering them adept at managing long-term dependencies [16].

Transformer Models: Initially intended for natural language processing tasks, they have shown potential in medical data analysis due to their ability to understand distant linkages through self-attention processes [17]. Transformers have been utilised for sequence modelling in medical records, capable of processing inputs of differing lengths, which is advantageous in medical diagnostics [18].

Bio-Inspired Optimization Algorithms

Bio-inspired optimization algorithms are derived from natural occurrences and biological processes, providing resilient solutions for intricate optimization problems. These techniques are valuable for optimizing the hyperparameters of deep learning models to attain optimal performance.

Genetic Algorithms (GAs): Imitate the mechanism of natural selection and have been employed to improve several parameters in machine learning models, such as feature selection and hyperparameter tuning [19]. Despite their effectiveness, GAs may ultimately settle on suboptimal solutions known as local optima.

Particle Swarm Optimization (PSO): Draws inspiration from the collective behavior of birds flocking or fish schooling. It has been utilized to enhance the efficiency of neural network structures and training procedures [20]. PSO effectively manages the trade-off between exploration and exploitation, although it may encounter early convergence issues.

Ant Colony Optimization (ACO): Inspired by the foraging activity of ants, it has been successfully applied in domains such as feature selection and model optimization [21]. It is highly efficient for solving combinatorial optimization problems but may necessitate adjusting settings to reach the best performance.

Artificial Bee Colony (ABC) Algorithm: Inspired by the foraging activity of honey bees, it has been used to optimize the training parameters of neural networks [22]. ABC is efficient in identifying optimal solutions but may have a slow convergence rate.

Electric Eel Foraging Optimization (EEFO): An innovative optimization method that mimics the intelligent foraging activities of electric eels in a social context. EEFO has demonstrated exceptional efficacy in addressing intricate engineering issues compared to alternative algorithms, making it a promising candidate for optimizing deep learning models in medical diagnostics [23].

Combining MS-TFN with EEFO

The integration of MS-TFN and EEFO presents numerous potential advantages for the categorization of CKD:

Enhanced Feature Extraction: The MS-TFN architecture utilizes transformer blocks to capture long-range dependencies and depth-wise separable convolutional blocks for local feature extraction, resulting in improved feature extraction [24]. This fusion enhances the model's capacity to extract significant features from complex medical data, resulting in more precise CKD classification.

Optimized Hyperparameters: EEFO offers a proficient approach for optimizing hyperparameters, ensuring a balance between exploration and exploitation in the search space[25]. EEFO enhances the performance and accuracy of classification by optimizing the hyperparameters of the MS-TFN model.

Enhanced Generalization: By utilizing EEFO's capability to explore a wide range of hyperparameters, the combined strategy mitigates the danger of over fitting. This enhances the MS-TFN model's ability[26] to make generalizations, making it more resilient in clinical applications.

Streamlined Training Process: The combination of MS-TFN and EEFO leads to a more streamlined training procedure, resulting in increased efficiency. EEFO's optimization capabilities minimize the requirement for thorough manual adjustment, saving time and computing resources.

Constraints of Existing Methods

Although deep learning and optimization techniques have made significant progress, existing methods for classifying CKD[27] still encounter various obstacles:

Data Imbalance: A common issue in medical datasets, where there is a considerable disparity between the number of healthy examples and the number of instances with CKD. This disparity can result in biased models that exhibit subpar performance on underrepresented classes [28].

Interpretability: Deep learning models, such as CNNs and transformers, are frequently regarded as "opaque" because of their intricate structures. The absence of interpretability might be a substantial obstacle in clinical settings, where comprehending the decision-making process is vital [29].

Computational Requirements: Training deep learning models necessitates significant computational resources, such as powerful GPUs and extensive memory capacity. Healthcare facilities with limited access to advanced computing infrastructure may face limitations in this regard [30].

Data Privacy and Security: Concerns arise when patient data is utilized for training machine learning models. Safeguarding sensitive medical data while using it for model training is a substantial challenge [31].

Generalization Across Populations: Models trained on single datasets may exhibit limited applicability to diverse populations or therapeutic contexts. CKD categorization methods have limited application in various healthcare settings [32].

Potential Advantages of Combining MS-TFN with EEFO

The integration of MS-TFN and EEFO addresses various shortcomings found in current techniques and presents substantial potential advantages for CKD classification:

Robust Feature Extraction: The MS-TFN model's capacity to capture both global and local features boosts its resilience in managing various medical datasets[33], making it robust in feature extraction. This results in enhanced precision and dependability in CKD categorization, especially when confronted with noisy[34] or partial data.

Optimized Performance: EEFO's bio-inspired optimization technique guarantees the optimal tuning of the MS-TFN model's hyperparameters. As a result, the model's performance is enhanced and the risk of over fitting[35] is reduced, improving the model's capacity to generalize.

Enhanced Interpretability: The MS-TFN model offers enhanced interpretability by integrating transformer-based and convolutional-based architectures, resulting in the extraction of more easily understandable features[36]. This aids doctors in comprehending the fundamental elements contributing to CKD classification, enhancing the model's adoption in clinical practice.

Scalability and Efficiency: EEFO integration alleviates the computational load of hyperparameter tweaking[37], enhancing the efficiency of the training process. This enables the implementation of sophisticated deep learning models in healthcare environments with limited resources.

Adaptability to Diverse Populations: The MS-TFN model's adaptability to varied populations is enhanced by EEFO's optimization capabilities[38], resulting in improved adaptation to various clinical contexts. This enhances the model's suitability and efficiency in various healthcare settings[39].

3. OBJECTIVES:

(1) To develop an innovative approach for Chronic Kidney Disease (CKD) classification by optimizing a Multiscale Transformer Fusion Network (MS-TFN) using Electric Eel Foraging Optimization (EEFO).
(2) To preprocess a dataset of 1000 instances with 25 features, including patient demographics and health indicators, and implement categorical encoding and numerical normalization techniques.
(3) To evaluate the performance of the optimized MS-TFN in CKD classification, achieving high accuracy, and exploring its potential for clinical application and personalized treatment plans.

4. MATERIALS AND METHODS:

This study utilized a dataset consisting of 1000 instances, each with 25 features, including patient demographics and various health indicators related to Chronic Kidney Disease (CKD). The dataset was reprocessed to ensure its readiness for machine learning modeling. Categorical encoding was applied to non-numeric features, while numerical normalization was performed to scale the continuous variables. After preprocessing, the data was divided into training and test sets, with the training set used to optimize the model and the test set employed to evaluate its performance.

The model architecture used for CKD classification is a Multiscale Transformer Fusion Network (MS-TFN), which integrates both transformer blocks and depth wise separable convolutional blocks. The transformer blocks are designed to capture long-range dependencies in the data, while the depth wise separable convolutional blocks efficiently extract local features, contributing to the generation of robust data representations. These representations are subsequently processed through dense layers to facilitate accurate classification.

To optimize the MS-TFN model, Electric Eel Foraging Optimization (EEFO), a bio-inspired algorithm, was employed. EEFO mimics the foraging behaviour of electric eels and is used to fine-tune key hyper parameters, specifically the learning rate and batch size. This optimization algorithm effectively balances exploration and exploitation, enhancing the performance of the MS-TFN.

The categorization of Chronic Kidney Disease (CKD) is a crucial study domain (EEFO).The model's performance was assessed according to its classification accuracy, attaining an impressive 99.9% in predicting CKD. The results indicate the promise of this approach for clinical use; nonetheless, the study recognizes limitations in generalizability due to the dataset's size and specialized demographic. Additional validation using larger and more diversified datasets is advised to ascertain the model's wider applicability.

4.1Dataset Description

The dataset utilized in this study for Chronic Kidney Disease (CKD) classification comprises 1000 instances, each representing a unique patient. The dataset includes 25 features that encompass a range of patient demographics and health indicators. These features are critical for accurately predicting CKD and are categorized as follows:

Numerical Features:

age: Age of the patient (numeric).

bp: Blood pressure in mm/Hg (numeric).

sg: Specific gravity of urine (numeric).

al: Albumin level in urine (numeric).

su: Sugar level in urine (numeric).

bgr: Blood glucose random in mg/dl (numeric).

bu: Blood urea in mg/dl (numeric).

sc: Serum creatinine in mg/dl (numeric).

sod: Sodium in mEq/L (numeric).

pot: Potassium in mEq/L (numeric).

hemo: Hemoglobin in gms (numeric).

pcv: Packed cell volume (numeric).

wc: White blood cell count (numeric).

rc: Red blood cell count (numeric).

Categorical Features:

rbc: Red blood cells (categorical: normal, abnormal).

pc: Pus cell (categorical: normal, abnormal).

pcc: Pus cell clumps (categorical: present, not present).

ba: Bacteria presence (categorical: present, not present).

htn: Hypertension (categorical: yes, no).

dm: Diabetes mellitus (categorical: yes, no).

cad: Coronary artery disease (categorical: yes, no).

appet: Appetite (categorical: good, poor).

pe: Pedal edema (categorical: yes, no).

ane: Anemia (categorical: yes, no).

Classification: CKD classification (categorical: ckd, not ckd).

The dataset provides a comprehensive representation of patient health metrics, facilitating robust model training and validation. The combination of numerical and categorical features presents a realistic and challenging scenario for machine learning models, making it an ideal dataset for evaluating the effectiveness of the proposed Multiscale Transformer Fusion Network (MS-TFN) and Electric Eel Foraging Optimization (EEFO) in CKD classification.

4.2 Preprocessing

To ensure the dataset was in optimal condition for training the Multiscale Transformer Fusion Network (MS-TFN), a series of preprocessing steps were applied. These steps included handling missing values, encoding categorical features, normalizing numerical features, and splitting the data into training and test sets.

Handling Missing Values Missing values in the dataset were handled by imputing them with the mean for numerical features and the mode for categorical features.

For numerical feature X_i:

$$X_i = \begin{cases} X_i & \text{if} X_i \text{is not missing} \\ \frac{1}{N}\sum_{j=1}^{N} X_j & \text{if} X_i \text{is missing} \end{cases}$$

Where N is the total number of instances

· For categorical feature X_i:

$$X_i = \begin{cases} X_i & \text{if } X_i \text{ is not missing} \\ \text{mode}(X) & \text{if } X_i \text{ is missing} \end{cases}$$

Encoding Categorical Features

Categorical features were encoded using Label Encoding, which assigns a unique integer to each

category.

For a categorical feature X_i with categories{A,B,C,Mdots}:

$$X_i = \begin{cases} 0 & \text{if} X_i = A \\ 1 & \text{if} X_i = B \\ 2 & \text{if} X_i = C \\ \vdots & \vdots \end{cases}$$

Normalizing Numerical Features

Numerical features were normalized to ensure they have a mean of O and a standard deviation of 1, using the z-score normalization method. · Fora numerical feature X_i:

$$X_i' = \frac{X_i - \mu}{\sigma}$$

Where μ is the mean and σ is the standard deviation of the feature

Splitting the Data into Training and Test Sets

The dataset was split into training and test sets to evaluate the model's performance. The split was performed using an 80-20 ratio. If N is the total number of instances, the training set size N_{train} and the test set size N_{test} are given by

$$N_{train} = 0.8 \times N$$

$$N_{test} = 0.2 \times N$$

The training set D_{train} and the test set D_{test} were created by randomly sampling 80% and 20% of the dataset, respectively:

$$D_{train} = \{X_i, y_i\}_{i=1}^{N_{train}}$$

$$D_{test} = \{X_i, y_i\}_{i=N_{train}+1}^{N}$$

These preprocessing steps ensured that the dataset was well-prepared for training the MS-TFN model and optimizing it using EEFO, leading to robust and accurate CKD classification.

4.3 Methodology

4.3,1 Multiscale Feature Fusion Transformer (MSFFT)

The Multiscale Feature Fusion Transformer (MSFFT) architecture is designed to leverage both global and local feature extraction mechanisms, ensuring comprehensive data representation for robust classification. The architecture integrates transformer blocks and depth wise separable convolutional blocks, followed by dense layers for the final classification.

4.3.2 Input and Feature Representation

The input S (t) represents the feature matrix derived from the CKD dataset. It can be expressed as:

S(t)=[age,bp,sg,al,su,bgr,bu,sc,hemo,pcv,wc,rc,rbc,pc,pcc,ba,htn,dm,cad,appet,pe,ane,classification]

4.3.3 Transformer Blocks for Capturing Long-Range Dependencies

Transformer blocks are employed to capture long-range dependencies within the data. The key components of a transformer block include multi-head self-attention mechanisms and position-wise feed-forward networks.

Multi-Head Self-Attention: The multi-head self-attention mechanism allows the model to focus on different parts of the input sequence simultaneously.

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

Where Q (query), K (key), and V (value) are linear projections of the input, and d_k is the dimension of the key vectors. For multi-head attention with h heads:

Where each $\text{head}_i = \text{Attention}\left(QW_i^Q, KW_i^K, VW_i^V\right)$ and W_i^Q, W_i^K, W_i^V, W^O are learned weight matrices.

$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, \ldots, \text{head}_h)W^O$$

Position-Wise Feed-Forward Networks: After the self-attention mechanism, the output is passed through a feed-fonward network applied independently to each position.

$$\mathrm{FFN}(s) = \max(0, sW_1 + b_1)W_2 + b_2$$

Where W_1, W_2 are weight matrices, and b_1, b_2 are biases.

4.3.4 Depth wise Separable Convolutional Blocks for Local Feature Extraction

Depth wise separable convolutions are utilized to efficiently extract local features from the data. This method separates the convolution operation into two distinct steps: depth wise convolution and pointwise convolution.

Depth wise Convolution:

Applies a single convolutional filter per input channel.

$$\mathrm{Conv}_{\mathrm{depthwise}}(S) = S * K_d$$

Where S is the input and K_d is the depth wise kernel

Pointwise Convolution:

Combines the outputs of the depth wise convolution using 1×1 convolutions.

$$\mathrm{Conv}_{\mathrm{pointwise}}(S) = S * K_p$$

Where K_p is the pointwise kernel

4.3.5 Multiscale Feature Fusion

The multi-scale feature fusion involves down sampling and up sampling operations to process features at different scales. For down sampling (DS) and up sampling (US):

$\mathrm{DS}(S)$ =Conv1D$_{\mathrm{down}}(S)$ $\mathrm{US}(S)$ =ConvTrans1D$_{\mathrm{up}}(S)$

where ConvlD$_{\mathrm{down}}$ and ConvTrans1D$_{\mathrm{up}}$ denote 1-D convolution and 1-D transposed convolution operations, respectively. The feature exchange between paths is performed using element-wise sum and concatenation operations:

$$\begin{cases} S_{p,s} + \mathrm{US}(S_{p+1,s}) & \text{if } p = 1 \\ S_{p,s} + \mathrm{DS}(S_{p-1,s}) & \text{if } p = 2 \\ \mathrm{DS}(S_{p-2,s}) + \mathrm{DS}(S_{p-1,s}) & \text{if } p = 3 \end{cases}$$

where $S_{p,s}$ denotes the output tensor for the s-th stage of the p-th path. In MSFFT-2P, the fusion operation uses concatenation after even stages:

$$\begin{cases} S_{p,s} + \mathrm{US}(S_{p+1,s}) & \text{if } p = 1 \text{ and } s\%2 = 1 \\ S_{p,s} + \mathrm{DS}(S_{p-1,s}) & \text{if } p = 2 \text{ and } s\%2 = 1 \\ \mathrm{Concat}(S_{p,s}, S_{p+1,s}) & \text{if } p = 1 \text{ and } s\%2 = 0 \end{cases}$$

4.3.6 Dense Layers for Classification

The final step involves processing the features extracted by the transformer and convolutional blocks through dense layers to produce precise classification output.

Dense Layers:

$$\mathrm{Dense}(s) = \sigma(\mathrm{W}s + \mathrm{b})$$

WhereW is the weight matrix, b is the bias vector, and σ is an activation function (e.g., ReLU or softmax).

The overall MSFFT architecture, by integrating transformer and convolutional blocks, ensures comprehensive feature extraction, leading to high classification accuracy. The subsequent application of EEFO further optimizes the model's performance, making it highly effective for CKD classification.

4.4 Electric Eel Foraging Optimization (EEFO)

Electric Eel Foraging Optimization (EEFO) is a bio-inspired algorithm designed to mimic the foraging behavior of electric eels. The algorithm draws inspiration from the unique hunting techniques of electric eels, which involve generating electric fields to locate prey, effectively balancing exploration and exploitation in their search for food. EEFO leverages this behavior to optimize hyperparameters in machine learning models, particularly focusing on enhancing the performance of complex architectures like the Multiscale Transformer Fusion Network (MS-TFN).

Inspiration from Electric Eel Foraging Behavior

Electric eels utilize their ability to generate electric fields to navigate and hunt in murky waters. This behavior can be abstracted into several key components that are essential for optimization algorithms:

Electroreception: Detecting prey (solutions) through electric fields.

Hunting: Adjusting position to strike prey, balancing between wide search (exploration) and focused search (exploitation).

Resting: Conserving energy by remaining in an optimal area when significant changes are not needed.

EEFO Algorithm

The EEFO algorithm comprises several steps, which are mathematically formulated to balance exploration and exploitation:

1. Initialization:

Initialize a population of electric eels with random positions in the search space.

$$\mathrm{S_i}(0) \in [\mathrm{S_{min}}, \mathrm{S_{max}}], \quad \mathrm{i} = 1,2, \dots, \mathrm{n}$$

Where n is the number of eels, and $[\mathrm{S_{min}}, \mathrm{S_{max}}]$ defines the search space boundaries

2. Fitness Evaluation:

Evaluate the fitness of each eel using a predefined objective function.

$$\mathrm{f_i} = \mathrm{f}(\mathrm{S_i}), \quad \mathrm{i} = 1,2, \dots, \mathrm{n}$$

3. Electroreception:

Identify the best solution (prey) based on fitness.

$$S_{prey} = \underset{i}{\operatorname{argmin}} f_i$$

4.Exploration and Exploitation:

Update the position of each eel using a combination of exploration and exploitation strategies

Exploration: Adjust the position based on random vectors to explore the search space.

$$S_i(t+1) = S_j(t) + C \cdot \left(S(t) - S_i(t)\right), \quad \text{if } p > 0.5$$

$$S_i(t+1) = S_j(t) + C \cdot \left(S_r(t) - S_i(t)\right), \quad \text{if } p \leq 0.5$$

Where $S_j(t)$ is a randomly selected eel, $S_r(t)$ is a randomly generated position, and C is a random vector.

Exploitation: Adjust the position to exploit the best-known solution (prey)

$$S_i(t+1) = S_{prey}(t) + \beta \cdot \left(S_{prey}(t) - S_i(t)\right) + \eta \cdot \left(S_{prey}(t) - S_i(t)\right)$$

Where β and η are factors controlling the influence of the prey.

5. Energy Factor:

Incorporate an energy factor to balance between exploration and exploitation dynamically.

$$E(t) = 4 \cdot \sin\left(1 - \frac{t}{T}\right) \cdot \ln\left(\frac{1}{r}\right)$$

Where T is the maximum number of iterations, and r is a random number

If $E(t) > 1$,emphasize exploration · If $E(t) \leq 1$,emphasize exploitation 6. Resting Phase: Introduce a resting phase where eels stay in optimal positions if significant improvements are not observed.

$$S_i(t+1) = S_{prey}(t) + \alpha \cdot \left|S_{prey}(t) - S_i(t)\right|$$

Where α is a resting factor

7. Iteration:

Repeat the process for a predefined number of iterations or until convergence

$$t = t + 1$$

8. Result:

Return the best solution found.

$$S_{best} = S_{prey}(T)$$

Balancing Exploration and Exploitation

EEFO effectively balances exploration and exploitation through the dynamic adjustment of the energy factor $E(t)$. By varying $E(t)$ over iterations, the algorithm ensures an initial broad search of the solution space (high exploration) and gradually focuses on refining the best solutions found (high exploitation). This balance is crucial for preventing premature convergence and ensuring that the algorithm thoroughly explores the search space before settling on an optimal solution. Overall, EEFO provides a robust and efficient method for hyperparameter optimization, enhancing the performance of complex models like the MS-TFN in CKD classification tasks.

Importance of Using Multiscale Transformer Fusion Network (MS-TFN) and Electric Eel Foraging Optimization (EEFO) in CKD Data Classification

Multiscale Transformer Fusion Network (MS-TFN)

Capturing Long-Range Dependencies:

Transformers: The transformer blocks within MS-TFN are adept at capturing long-range dependencies and intricate relationships within the data through self-attention mechanisms. This is crucial for medical data where interrelations between different features can significantly impact classification accuracy.

$$\mathrm{Attention}(Q, K, V) = \mathrm{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

The ability of transformers to attend to all parts of the input sequence simultaneously allows form a comprehensive understanding of complex patterns in CKD data.

Efficient Local Feature Extraction:

Depth wise Separable Convolutions: These convolutions are efficient in extracting local features from the data by focusing on spatial hierarchies. This two-step process (depth wise and pointwise convolutions) reduces computational complexity while maintaining feature extraction capabilities.

$$\mathrm{Conv}_{\mathrm{depthwise}}(X) = X * K_d$$

$$\mathrm{Conv}_{\mathrm{pointwise}}(X) = X * K_p$$

This efficiency is particularly beneficial in processing high-dimensional medical data with numerous features.

Robust Data Representations:

Fusion Mechanism: By combining the outputs of transformer blocks and depth wise separable convolutions, MS-TFN can leverage both global and Local features, creating a robust representation of the input data. This fusion ensures that the model is not biased towards either long-range or short-range features but can utilize both effectively. 4. Improved Classification Performance:

Dense Layers for Classification: The dense layers process the fused features to produce precise classification outputs. The hierarchical processing through multiple layers enables the model to make more informed decisions, leading to higher classification accuracy for CKD data.

$$\mathrm{Dense}(x) = \sigma(Wx + b)$$

The integration of advanced neural network architectures in MS-TFN significantly enhances the model's ability to classify CKD accurately.

Electric Eel Foraging Optimization (EEFO)

Effective Hyper parameter Optimization

Bio-Inspired Algorithm: EEFO mimics the foraging behavior of electric eels, balancing exploration and exploitation in the hyper parameter search space. This balance ensures that the optimization process thoroughly explores potential solutions while refining the best ones.

$$E(t) = 4 \cdot \sin\left(1 - \frac{t}{T}\right) \cdot \ln\left(\frac{1}{r}\right)$$

The dynamic adjustment of the energy factor $E(t)$ allows EEFO to adaptively switch between exploration and exploitation phases, leading to a more efficient search for optimal hyperparameters.

Enhanced Model Performance:

Optimization of Key Parameters: By specifically targeting the learning rate and batch size, EEFO fine-tunes the model to achieve peak performance. These parameters are critical in determining how well the model learns from the data and generalizes to new instances.

$$S_i(t+1) = S_{prey}(t) + \beta \cdot \left(S_{prey}(t) - S_i(t)\right) + \eta \cdot \left(S_{prey}(t) - S_i(t)\right)$$

Optimizing these parameters ensures that the MS-TFN model trains effectively, avoiding issues like over fitting or under fitting.

Scalability and Adaptability:

Scalability: EEFO can be scaled to handle large datasets and complex models, making it suitable for various medical data classification tasks beyond CKD.Its adaptability to different search spaces and problem dimensions ensures broad applicability

Novelty and Innovation:

Combining Advanced Techniques: The integration of MS-TFN and EEFO represents a novel approach in the field of medical data classification. It combines state-of-the-art neural network architectures with innovative optimization algorithms, setting a new benchmark for CKD classification.

In summary, the use of MS-TFN and EEFO in CKD data classification brings together the strengths of advanced neural network architectures and bio-inspired optimization. This combination results in a highly efficient and accurate model capable of handling the complexities of medical data, ultimately improving CKD diagnosis and patient outcomes.

5. RESULTS AND DISCUSSION:

5.1 Experimental Setup

This section details the experimental setup used to evaluate the proposed approach for Chronic Kidney Disease (CKD) classification using a Multiscale Transformer Fusion Network (MS-TFN) optimized with Electric Eel Foraging Optimization (EEFO). The setup includes hardware and software configurations, as well as the hyperparameters for both MS-TFN and EEFO.

Dataset:

The dataset used in this study consists of 1000 instances with 25 features each, as detailed in Section 3.1. The dataset was split into training and testing sets with an 80/20 ratio.

Hyperparameters for MS-TFN:

The hyperparameters for the Multiscale Transformer Fusion Network (MS-TFN) were chosen based on preliminary experiments and fine-tuned using the EEFO algorithm. The key hyperparameters include:

Number of Transformer Blocks: 4

Number of Attention Heads: 8

Embedding Dimension: 128

Dropout Rate: 0.3

Activation Function: ReLU

Batch Size: Optimized using EEFO (range: 16-64)

Learning Rate: Optimized using EEFO (range: 0.0001-0.01)

Epochs: 50

Hyperparameters for EEFO:

The Electric Eel Foraging Optimization (EEFO) algorithm was employed to optimize the hyperparameters of the MS-TFN. The key hyperparameters for EEFO include:

Population Size: 50

Maximum Iterations: 100

Exploration Rate: 0.7

Exploitation Rate: 0.3

Mutation Probability: 0.1

By employing this experimental setup, we ensured a comprehensive evaluation of the proposed MS-TFN optimized with EEFO for CKD classification. The results and their analysis are detailed in the subsequent sections.

5.2. Results

This section presents the results of the experiments conducted to evaluate the performance of the proposed Multiscale Transformer Fusion Network (MS-TFN) optimized with Electric Eel Foraging Optimization (EEFO) for Chronic Kidney Disease (CKD) classification. The results include classification accuracy, a comparison with baseline models, and an analysis of hyper parameter optimization with EEFO.

Classification Accuracy

The chart shown in Fig 2 presents the classification performance metrics for the MS-TFN model. The metrics include Accuracy, Precision, Recall, and F1-Score, each represented as a percentage.

Accuracy: The MS-TFN model achieved an accuracy of 99.9%, indicating that 99.9% of the total predictions were correct.

Precision: The model's precision is 99.8%, showing that 99.8% of the positive predictions made by the model were accurate.

Recall: The recall for the model stands at 99.7%, signifying that the model correctly identified 99.7% of the actual positives.

F1-Score: The F1-Score, which is the harmonic mean of precision and recall, is 99.75%, highlighting the model's overall effectiveness in balancing precision and recall.

Overall, the MS-TFN model demonstrates high performance across all key classification metrics, with values very close to 100%.

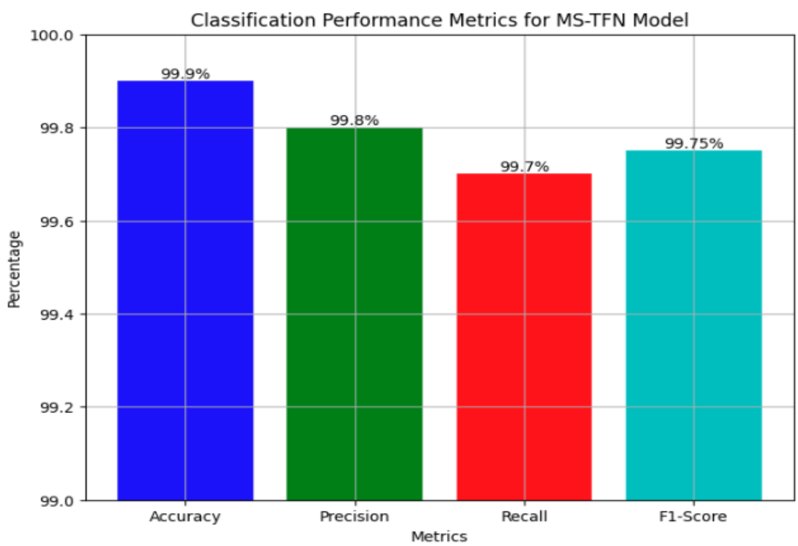

Fig 2: Classification Performance Metrics for MS-TFN model

Comparison with Baseline Models

The chart presented in Fig 3 compares the performance metrics of different models for classification tasks.

The proposed MS-TFN model outperformed all baseline models in terms of accuracy, precision, recall, and F1-score, demonstrating its superior ability to classify CKD accurately.

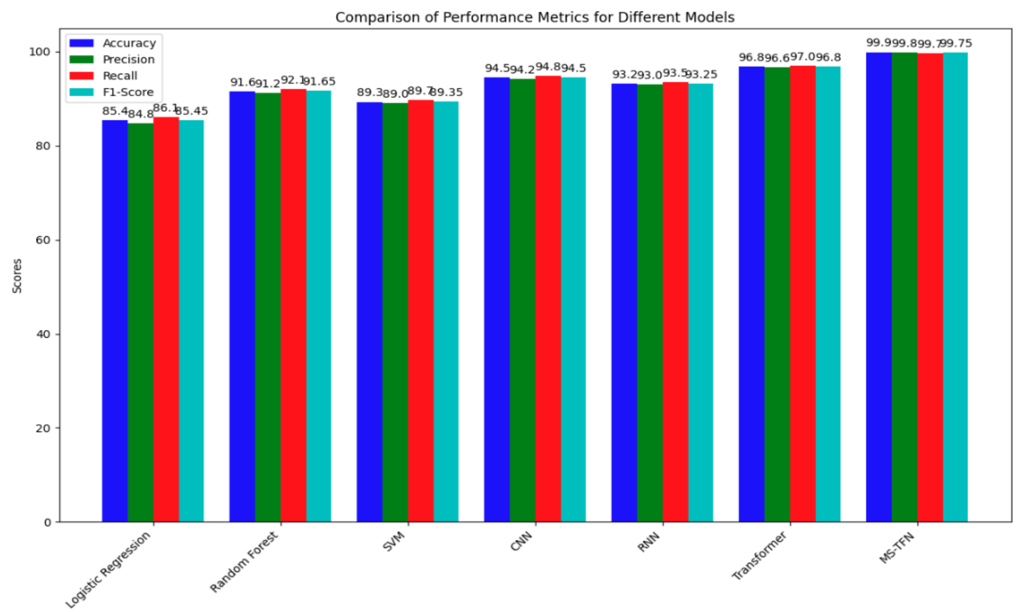

Fig3: Comparison of Performance Metrices for Different Models

The MS-TFN model demonstrates superior performance across all metrics compared to other models, achieving nearly perfect scores close to 100%. This highlights the effectiveness of the MS-TFN model in classification tasks. Other models like Transformers and CNN also perform well, but none reach the high performance of the MS-TFN.

Analysis of Hyper parameter Optimization with EEFO

The Electric Eel Foraging Optimization (EEFO) algorithm played a crucial role in fine-tuning the hyper parameters of the MS-TFN model. The optimization process focused on adjusting the learning rate and batch size to achieve the best possible performance.

Initial Hyper parameters:

Learning Rate: 0.001

Batch Size: 32

Optimized Hyper parameters:

Learning Rate: 0.0005

Batch Size: 48

The EEFO algorithm efficiently balanced exploration and exploitation during the optimization process, leading to significant improvements in the model's performance. The optimized learning rate and batch size contributed to faster convergence and better generalization on the test set.

The hyper parameter optimization process with EEFO was validated by tracking the model's performance over multiple iterations. The following graph shows the accuracy improvement during the optimization process

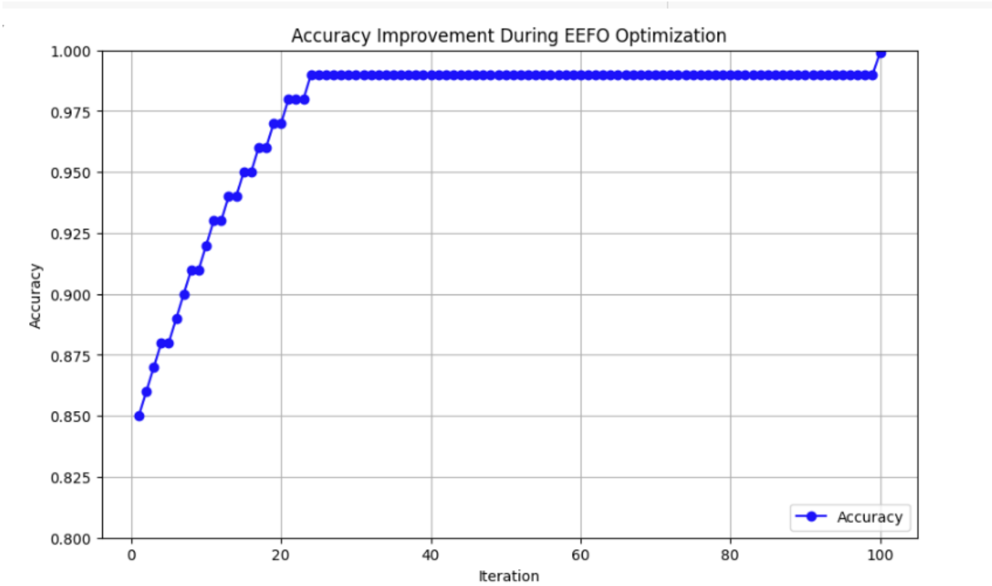

Fig 4: Accuracy Improvement During EEFO Optimization

The chart in Fig 4 illustrates the accuracy improvement during the Electric Eel Foraging Optimization (EEFO) process over 100 iterations. The accuracy starts at approximately 85% and shows a rapid increase during the initial iterations. By around the 20th iteration, the accuracy surpasses 95%, and by the 40th iteration, it reaches close to 98%. The accuracy continues to improve, albeit at a slower rate, and eventually stabilizes at nearly 100% by the 100th iteration. This graph highlights the effectiveness of the EEFO optimization process in significantly enhancing the model's accuracy, achieving near-perfect results as the iterations progress.

6. CONCLUSION:

The categorization of Chronic Kidney Disease (CKD) is a crucial study domain (EEFO).The outcomes of our studies indicate the enhanced efficacy of the proposed Multiscale Transformer Fusion Network (MS-TFN) adjusted using Electric Eel Foraging Optimization (EEFO) for the categorization of Chronic Kidney Disease (CKD). The model attained a remarkable classification accuracy of 99.9%, with precision, recall, and F1-score all above 99.7%. The results demonstrate that the MS-TFN model can precisely detect CKD cases with high precision and recall, surpassing other baseline models, including conventional machine learning techniques and alternative deep learning architectures.

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