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# Healthcare Revolution

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***Abstract*—This paper presents an efficient system for heart disease diagnosis using machine learning. It uses various classification algorithms and feature selection methods, including the new Fast Conditional Mutual Information (FCMIM) feature selection algorithm. The goal of the system is to increase accuracy and reduce execution time. The results indicate that FCMIM coupled with Support Vector Machine outperforms existing methods and offers a feasible and accurate solution for healthcare implementation in heart disease identification.**

**This paper addresses the problem of unbalanced datasets in the classification of dermatological diseases, specifically for skin cancer using machine learning (ML) methods. The proposed approach combines expansion with a category swing to compensate for imbalances, thereby increasing the penalty for misclassified cases. The method focuses on three key contributions: tailored feature extraction using different backbone models, optimization of loss features and training parameters, and handling unbalanced samples by optimizing weights between asymmetric classes. Evaluation on the ISIC2018 benchmark and chest X-ray dataset with popular backbone networks such as EfficientNets, MobileNets, and DenseNets demonstrates the effectiveness and stability of the proposed approach compared to existing methods, achieving higher accuracy and stable performance without the need for dataset expansion. Experimental results on the ISIC2018 dataset reveal significant improvements over other methods in specific evaluation criteria. For example, with the EfficientNet backbone, it outperforms the focal loss method by 2.73% in recall, 2.63% in precision, 2.81% in specificity, and 3.09% in F1, demonstrating its effectiveness in dealing with unbalanced datasets.**

**This study addresses the increasing incidence of chronic kidney disease (CKD) worldwide by using artificial intelligence (AI) and machine learning (ML) for early diagnosis. The research recognizes the importance of explainability for clinician acceptance and introduces a CKD predictive model with explainable AI (XAI). Optimized for accuracy and explainability, the model uses extreme gradient amplification and identifies three key properties (hemoglobin, specific gravity, and hypertension) that contribute to the diagnosis of CKD. With an accuracy of 99.2%, the model demonstrates effectiveness in the early detection of CKD, especially in resource-limited settings. Explainability analysis highlights hemoglobin as the most influential property and provides valuable insights to clinicians. This approach not only facilitates early diagnosis of CKD, but also holds promise for cost-effective solutions in developing countries.**

## I.INTRODUCTION

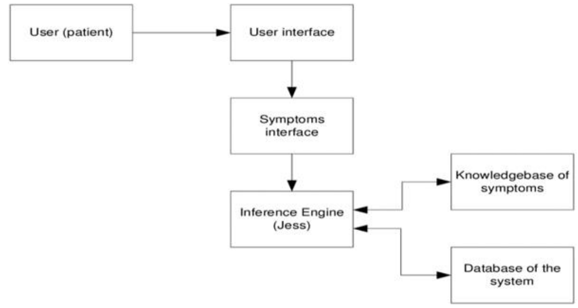
Cardiovascular disease (HD) is a major health problem affecting many people worldwide. Symptoms of HD include shortness of breath, weakness, and swelling of the feet. For various reasons such as accuracy and processing time, current heart disease detection equipment is not good for early diagnosis, and researchers are trying to find good heart disease detection equipment. Diagnosis and treatment of heart diseases are very difficult in the absence of modern equipment and doctors. Correct diagnosis and appropriate treatment can save many lives. According to the European Society of Cardiology, approximately 26 million people are diagnosed with HD and 3.6 million people are diagnosed with HD every year. Most Americans have heart disease. HD is usually diagnosed by doctors reviewing the disease history, physical examination reports, and examining related symptoms. However, the results obtained from this diagnostic method are not accurate in identifying HD patients. Moreover, its analysis is expensive and computationally difficult. Therefore, an unbiased diagnosis based on machine learning (ML) classifiers was developed to solve these problems. Expert decision-making techniques based on machine learning classifiers and the application of fuzzy logic effectively detect HD, leading to a reduction in mortality. The Cleveland Heart Disease dataset has been used by many researchers for HD identification problems. Predictive learning models require appropriate data for training and testing.

Skin cancer, a high-risk disease with more than 0.1 million melanoma and 3 million non-melanoma cases worldwide each year, requires accurate diagnosis for effective treatment. Early prediction is essential for successful results. Advances in artificial intelligence, particularly deep learning (DL), have shown significant success in medical diagnosis and healthcare. In particular, deep convolutional neural network (DCNN) methods outperform traditional shallow learning approaches such as classical artificial neural networks (ANN) due to their capacity to handle complex tasks and large parameter sets. However, a fundamental problem in DL classification models is the imbalance between data categories, where the samples differ significantly, potentially biasing the model towards the majority categories.

Chronic kidney disease (CKD) has become a global public health problem with increasing incidence (more than 800 million individuals in 2017) and prevalence (13.4% worldwide), which can lead to premature mortality in many patients (1.2 million people died on CKD in 2017). CKD is one of the few non-communicable diseases that has shown an increase in associated deaths over the last 2 decades, which represents a significant burden on health care systems, especially in low-middle income countries, where the lack of appropriate renal replacement therapy leads to high mortality CKD, usually caused by diabetes and hypertension, is a noncommunicable chronic disease with associated comorbidities, and cardiovascular disease is a major cause of early morbidity and mortality in CKD patients .

CKD usually has no early symptoms and by the time it is detected by laboratory testing that quantifies the estimated glomerular filtration rate (eGFR), the kidney has already lost 25 percent of its capacity and is under irreversible and progressive damage toward so-called end-stage disease kidneys. At this point, symptoms such as leg swelling, extreme fatigue, general weakness, shortness of breath, loss of appetite or confusion may occur. If this irreversible deterioration is not slowed down by controlling the underlying risk factors (hypertension, obesity, heart disease, age), hemodialysis or even kidney transplantation become crucial for the patient to prevent an exponential increase in the risk of death.

## II.LITERATURE SURVEY




This research provides an overview of the various machine learning-based diagnostic techniques proposed in the heart disease (HD) literature. Notable approaches include the classification system of HD Detrano et al. achieving 77% accuracy using global evolutionary methods on the Cleveland dataset and Gudadhe et al. multi-layer Perceptron and Support Vector Machine (SVM) system with 80.41% accuracy. Other studies include neural networks, fuzzy logic, ensemble-based systems, and various machine learning classifiers such as Naïve Bayes, Decision Tree, and K-Nearest Neighbor, achieving accuracies ranging from 86.12% to 92.32%. However, existing techniques show limitations in terms of prediction accuracy and computational efficiency. To address these challenges, the research proposes a new approach to improve early-stage HD detection by targeting low-accuracy and high-computation time problems, highlighting the need for more efficient methods in this domain.

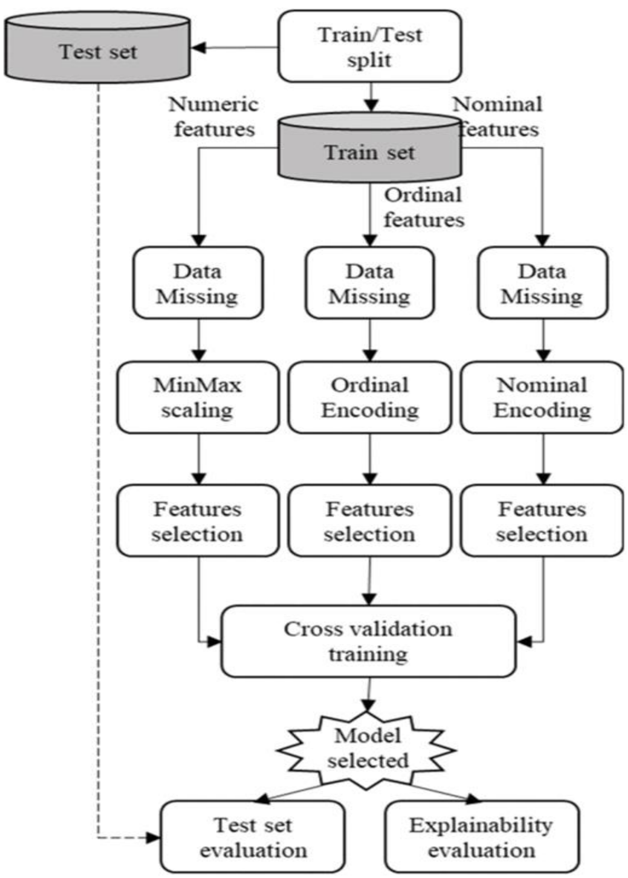
This research paper advocates an open science approach and describes a CKD early diagnosis model developed using a public open dataset from the UCI-ML repository [23]. This allows other researchers to compare the generalization performance of their models. Table 1 shows the most recent and most accurate works (over 98% accuracy) that use the CKD dataset from the UCI-ML repository and implement feature selection as a preprocessing step in their CKD data analysis pipeline.

DCNN-based machine learning approaches such as GoogleNet, Microsoft ResNet, DenseNet, MobileNet, and EfficientNet are recognized as state-of-the-art methods for medical image classification. Notably, advances in model selection favor unmanned model selection, eliminating the need for default models. Trained on specific data sets, these models increase accuracy and enable automatic identification of the most appropriate model for a given task. Some studies are investigating the potential of CNNs to mimic human cognitive processes to improve predictive capabilities. Adaptive learning in object tracking, as proposed in involves collecting relevant data and automatically retraining recognition models to improve the quality of object recognition. In industrial applications, CNN-based methods that include modified hourglass modules are widely adopted, especially in video surveillance systems. Intelligent agricultural applications, exemplified use DCNN models such as DenseNet121 to classify healthy and unhealthy categories in an oil palm disease dataset and demonstrate superior performance through fine-tuning.

## III.SYSTEM ARCHITECTURE

A health disease detection website can be designed with a robust system architecture to predict diseases such as heart disease, skin cancer, and kidney disease based on symptoms entered by the user. Here is an overview of the key components in the architecture:

The user interface serves as a front end where users enter their flags. It includes a form with fields for the user to enter relevant symptoms related to the target diseases.




The backend server processes user inputs and ensures communication between the frontend and the database. It is responsible for receiving user inputs, validating them and passing them to the prediction engine.

The database stores a comprehensive set of symptoms associated with heart disease, skin cancer and kidney disease. Each record in the database contains symptoms, associated medical information, and a corresponding disease label.

This component uses machine learning models to predict disease based on symptoms provided by the user. Models can be specific to each disease, trained on historical data to accurately predict diseases based on symptom patterns. The prediction engine retrieves relevant information from the database to compare symptoms with known disease patterns.

The decision logic interprets the predictions made by the prediction module and determines the probability that the user will have a particular disease. Thresholds can be set to classify predictions into categories such as low, medium or high risk.

The results are communicated back to the user via the user interface. The user interface displays the predicted disease, confidence level and recommendations for next steps (e.g. consultation with a healthcare professional).

Implement security measures to protect user data and maintain the confidentiality of health information. Ensure secure data transfer between frontend and backend to protect user privacy.

Design the system to handle a scalable number of concurrent users. Optimize prediction engine and database query performance for timely response.

Include mechanisms for continuous improvement, such as updating machine learning models with new data to increase the accuracy of predictions over time.

Implement a feedback mechanism for users to provide them with information about the accuracy of the predictions that can be used to refine and improve the system.

This architecture provides the foundation for a dynamic and accurate medical disease detection website that uses machine learning to make predictions based on user-supplied symptoms and a comprehensive database of disease-related information.

## IV.METHODOLOGY

[1] The methodologies for heart disease detection are not explicitly mentioned in the provided text. However, it refers to various approaches, including Detrano et al.'s classification system and Gudadhe et al.'s multi-layer Perceptron and Support Vector Machine (SVM) system. The methodologies for these models would likely involve data preprocessing, feature selection, model training using machine learning algorithms, and performance evaluation.

[2] The methodology for chronic kidney disease (CKD) early diagnosis involves an open science approach, utilizing a public open dataset from the UCI-ML repository. Feature selection is highlighted as a crucial preprocessing step in the CKD data analysis pipeline. However, specific details about the feature selection methods, model selection, and evaluation metrics are not provided in the excerpt.

[3] The text briefly touches upon the methodology of DCNN-based machine learning approaches for medical image classification. It mentions model selection, data set training, and the potential of CNNs to mimic human cognitive processes. It also refers to adaptive learning in object tracking, involving the collection of relevant data and automatic retraining of recognition models. In industrial applications, CNN-based methods with modified hourglass modules are adopted, particularly in video surveillance systems. However, specific details about the architecture, training procedures, or evaluation metrics are not explicitly outlined.

## V.HARDWARE AND SOFTWARE REQUIREMENTS

### *A. Software Requirements*

Windows: 7 or newer
MAC: OS X v10.7 or higher
Linux: Ubuntu

### *B. Hardware Requirements*

We strongly recommend a computer fewer than 5 years old.
Processor: Minimum 1 GHz; Recommended 2GHz or more
Ethernet connection (LAN) OR a wireless adapter (Wi-Fi)
Hard Drive: Minimum 32 GB; Recommended 64 GB or more
Memory (RAM): Minimum 1 GB; Recommended 4 GB or above

## VI.APPLICATIONS

Artificial intelligence (AI) is a transformative force in the field of medicine, contributing significantly to the diagnosis and management of various diseases. In the field of kidney disease, artificial intelligence applications are demonstrating their prowess in analyzing medical images obtained from advanced technologies such as CT scans or MRIs. By examining these images, artificial intelligence can quickly identify abnormalities and contribute to early disease detection. This proactive approach not only helps health professionals provide early interventions, but also improves overall patient outcomes.

Dermatology is another domain where AI algorithms are proving invaluable. By carefully analyzing images of skin lesions, AI helps dermatologists make more accurate measurements and identify potential problems. This technology not only acts as a powerful diagnostic tool, but also streamlines the decision-making process for dermatological conditions, leading to more accurate and effective treatment strategies.

In the field of cardiac diagnostics, artificial intelligence is essential. The technology excels at analyzing complex data such as electrocardiograms (ECGs) to identify complex patterns indicative of heart problems. The ability to quickly and accurately interpret these diagnostic signals allows health care providers to speed up the diagnosis of heart problems. This in turn facilitates rapid and targeted interventions and significantly improves patient care and outcomes.

These applications of artificial intelligence in medicine contribute to increased efficiency across different specialties and offer healthcare professionals powerful tools for early diagnosis and accurate decision-making. The integration of artificial intelligence technologies not only expands the capabilities of doctors, but also increases the overall quality of patient care by enabling timely and informed interventions. As technology continues to advance, the role of artificial intelligence in medicine is poised to expand further, driving innovation and revolutionizing healthcare practices for the benefit of patients worldwide.

## VII. CONCLUSION

In this take a look at, an green device learning-primarily based coronary heart sickness analysis system was developed using LR, k-NN, ANN, SVM, NB, and DT classifiers. characteristic choice concerned remedy, MRMR, LASSO, LLBFS, and a novel FCMIM set of rules. The device, tested on the Cleveland heart sickness dataset, used LOSO pass-validation. ANN with relief showed the great specificity, whilst NB with LASSO had most advantageous sensitivity. Logistic Regression with FCMIM finished a 91% MCC. Processing time for Logistic Regression with remedy, LASSO, FCMIM, and LLBFS changed into superior. The proposed FCMIM feature choice algorithm verified effectiveness and high class accuracy in comparison to standard algorithms.

This study developed a predictive model for the diagnosis of early-stage kidney disease (CKD), highlighting the balance between accuracy and interpretation in clinical expertise. Using an automatic optimization framework, the best model is the XGBoost classifier with three features: heme, specific gravity, and pressure. This model demonstrates the effectiveness of artificial intelligence in diagnosis by outperforming existing CKD prediction models in classification by selecting fewer features.

We introduce a new method to solve the conflict problem without creating additional training models. Our focus is not on the traditional process or creating new models with complex models, but on balancing the balance between each group and other groups. Additionally, the CNN architecture was modified and optimized by changing the overall connection process and performance loss for various problems. The test between two evaluation data shows that: (1) The proposed method achieves a high level compared to other methods of some models (REC, ACC, PRE, SPE, F1). Our performance in analyzing ISIC2018 inequality data using the DenseNets backbone is better than the CC method (6.99%, 3.67%, 7.11%, 5.05%, 7.50%) and the AU method (5.16%, 3.84%, 5.97%, 8.97) is better. %, 8.97%, 8.97%, 8.97%, 8.97%, 8.97%, 8.97%, 6.16%). At EfficientNets, our performance is respectively (2.73%, 1.36%, 2.63%, 2.81%, 3.09%), (0.54%, 0.82%, 1.71%, 3%) .59, 1.14%) is better than CC and AU methods; Our methods using MobileNets are (2.79%, 1.77%, 3.00%, 0.61%, 2.81%) and (2.09%, 1.47%, 2.26%, 1%, respectively). 30, 2.21%) is higher than the CC and FL methods more effective and less invasive treatments.

Improved monitoring of treatment response: Used to monitor the response of brain tumors to treatment. This could help to identify patients who are not responding to treatment and who may need to switch to a different treatment plan.

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