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Full Length Article

Advancing Kidney Tumor Detection in CT Scans with a Hybrid Computational Framework

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ABSTRACT
Kidney diseases such as cysts, tumors, and stones are life-threatening conditions that require early and accurate detection for effective treatment. Traditional diagnostic methods using CT scans often depend on manual interpretation by radiologists, which can be time-consuming and prone to error. To address this challenge, we propose a deep learning–based automated system for multi-class kidney disease classification using CT images. The system utilizes EfficientNetV2B0, a state-of-the-art convolutional neural network, to extract deep features from CT scans. A custom classification head with Global Average Pooling, Dropout, and Dense layers is employed to classify images into four categories: Normal, Cyst, Tumor, and Stone. Data augmentation and class weighting are applied to handle dataset imbalance and improve generalization. The model achieves high accuracy and robustness, outperforming conventional CNN approaches. Furthermore, the trained model is integrated into a Flask web application, providing a user-friendly interface with functionality for image upload, real-time prediction with confidence scores, and visualization of training results through charts. This approach demonstrates the potential of advanced deep learning models combined with web deployment to support radiologists in fast, reliable, and scalable kidney disease diagnosis.

Keywords: *Kidney Disease, Deep Learning, CT Imaging, EfficientNetV2B0, CNN, Medical Diagnosis, Image Classification, Data Augmentation, Web Application*

Introduction:
Kidney-related disorders, including cysts, tumors, and kidney stones, are among the most prevalent health concerns worldwide and can significantly impact a patient's quality of life. In severe cases, delayed diagnosis or improper treatment may lead to chronic kidney disease or complete renal failure. Early identification of these conditions is therefore essential to ensure timely medical intervention and improve patient outcomes. Among the available diagnostic techniques, Computed Tomography (CT) imaging is widely preferred due to its ability to provide detailed cross-sectional views of internal organs, allowing clinicians to detect even subtle abnormalities in kidney structure.
Despite its effectiveness, manual analysis of CT images presents several challenges. Radiologists are often required to examine a large number of scans, which can be both time-consuming and mentally demanding. This increases the likelihood of human error, particularly in complex cases or under high workload conditions. Moreover, accurate interpretation requires significant expertise, making consistent diagnosis difficult across different healthcare settings.
Recent advancements in Artificial Intelligence (AI), especially in deep learning and computer vision, have opened new possibilities for automating medical image analysis. Convolutional Neural Networks (CNNs) have shown remarkable performance in extracting meaningful patterns from medical images and assisting clinicians in diagnosis. In this work, a deep learning–based framework is proposed for the multi-class classification of kidney CT images into four categories: Normal, Cyst, Tumor, and Stone.
The proposed system utilizes EfficientNetV2B0, a modern CNN architecture known for its efficiency and strong feature extraction capability. The model is pre-trained on large-scale datasets and then fine-tuned using kidney CT images to adapt it to the specific classification task. To improve performance and handle practical challenges such as limited data and class imbalance, techniques including data augmentation, class weighting, and dropout regularization are incorporated.

In addition to model development, the system is deployed through a Flask-based web application, providing a user-friendly interface for real-time prediction. Users can upload CT images and receive classification results along with confidence scores, making the system accessible and practical for clinical support. This integration of advanced deep learning techniques with an interactive application demonstrates a step toward more efficient, accurate, and scalable kidney disease diagnosis.

LITERATURE REVIEW (Expanded)

Recent research in medical image analysis has increasingly focused on the application of machine learning and deep learning techniques for disease detection and classification. Mahmud et al. (2023) presented a hybrid approach that combines CT imaging data with clinical metadata for kidney cancer diagnosis. By integrating multiple data sources, their model was able to capture more comprehensive information, leading to improved tumor classification accuracy. This study highlights the importance of multi-modal data in enhancing diagnostic performance.

Yang et al. (2024) investigated various data augmentation strategies aimed at improving model robustness. Their findings show that carefully designed augmentation techniques—such as transformations that preserve image characteristics while introducing diversity—can significantly enhance model generalization, particularly when dealing with small or imbalanced datasets. This is highly relevant in medical imaging, where collecting large datasets is often challenging.

Hastuti et al. (2021) explored the use of transfer learning with DenseNet121 for medical image classification. Their work demonstrated that pre-trained models can achieve high accuracy even with limited training data, as they leverage previously learned features from large datasets. This approach reduces training time and computational cost while maintaining strong performance, making it suitable for healthcare applications.

Although these studies contribute valuable insights, they primarily emphasize improving classification accuracy. Many existing approaches do not fully address issues such as real-time deployment, multi-class classification, and dataset imbalance. Furthermore, the practical integration of such models into user-friendly systems remains limited. These gaps highlight the need for a comprehensive solution that combines accurate classification with real-time usability and efficient handling of imbalanced data.

METHODOLOGY

1. Data Collection and Pre-processing

The first stage involves collecting kidney CT scan images from reliable datasets. The images are categorized into four classes: Normal, Cyst, Tumor, and Stone. To ensure consistency, all images are resized to a fixed dimension and normalized so that pixel values fall within a standard range. Noise removal and basic cleaning techniques are also applied to improve image quality. These preprocessing steps are essential for providing uniform and high-quality input to the model, which directly impacts classification performance.

2. Data Augmentation

Medical datasets are often limited in size and may contain class imbalances. To address this issue, data augmentation techniques are applied to artificially increase dataset diversity. Transformations such as rotation, horizontal and vertical flipping, scaling, and brightness adjustment are used to generate new variations of existing images. This helps the model learn more generalized features and reduces the risk of overfitting.

3. Feature Extraction using EfficientNetV2B0

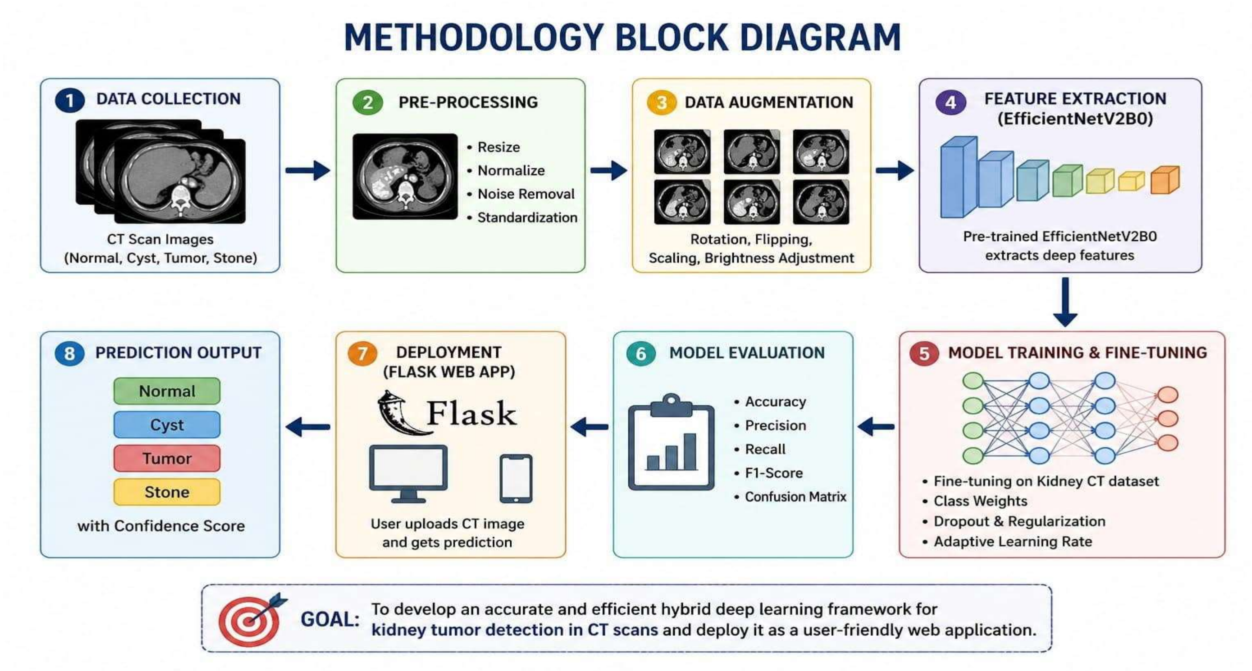
EfficientNetV2B0 is employed as the core feature extraction model. This architecture is designed to achieve high performance while maintaining computational efficiency. By leveraging transfer learning, the model utilizes knowledge gained from large-scale datasets and applies it to kidney CT image classification. It effectively captures both low-level features (such as edges and textures) and high-level features (such as shapes and patterns), which are crucial for distinguishing between different kidney conditions.

4. Model Training and Evaluation

The model is trained using fine-tuning techniques, where the later layers of the network are adjusted to better fit the kidney dataset. To prevent overfitting, dropout regularization is applied, and class weighting is used to handle imbalanced data distribution. The model's performance is evaluated using multiple metrics, including accuracy, precision, recall, and F1-score. A confusion matrix is also used to analyze classification results in detail, providing insights into correct and incorrect predictions across all classes.

5. Web Application Deployment

To make the system accessible and practical, the trained model is integrated into a Flask-based web application. This interface allows users to upload CT scan images and receive predictions in real time. The application displays the predicted class along with confidence scores, helping users understand the reliability of the results. In addition, visual outputs such as performance graphs can be included to provide further insights. This deployment step ensures that the developed model can be used beyond a research environment and applied in real-world clinical settings.



IMPLEMENTATION

The proposed system is implemented using Python with TensorFlow/Keras. The EfficientNetV2B0 pre-trained model is used for feature extraction and classification of kidney CT images into four classes: Normal, Cyst, Tumor, and Stone.

The dataset is pre-processed through resizing and normalization, and data augmentation techniques are applied to improve generalization. A custom classification layer is added to the base model, and the network is trained using appropriate optimization techniques to enhance performance.

The trained model is then integrated into a Flask-based web application, enabling users to upload CT images and obtain real-time predictions with confidence scores.

TESTING

The proposed system is evaluated using multiple testing strategies to ensure accuracy, reliability, and efficiency.

Unit Testing:

Individual components such as data pre-processing, augmentation, model loading, and prediction modules are tested independently to ensure correct functionality and output.

Functional Testing:

The system is tested with valid and invalid CT scan inputs to verify correct classification into Normal, Cyst, Tumor, and Stone categories. Output predictions and confidence scores are validated against expected results.

Integration Testing:

All modules, including data processing, model prediction, and Flask interface, are integrated and tested to ensure seamless interaction without errors.

Performance Testing:

The system is evaluated for response time and efficiency. The model provides predictions within acceptable time limits, ensuring real-time usability.

System Testing:

The complete application is tested as a whole to verify that it meets all functional requirements and performs reliably under different conditions.

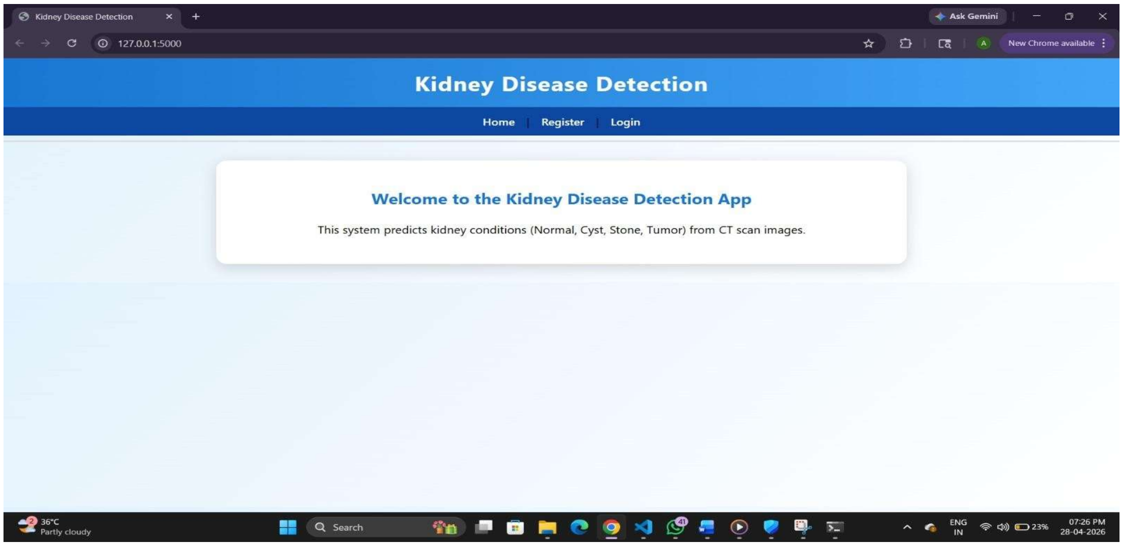
User Acceptance Testing:

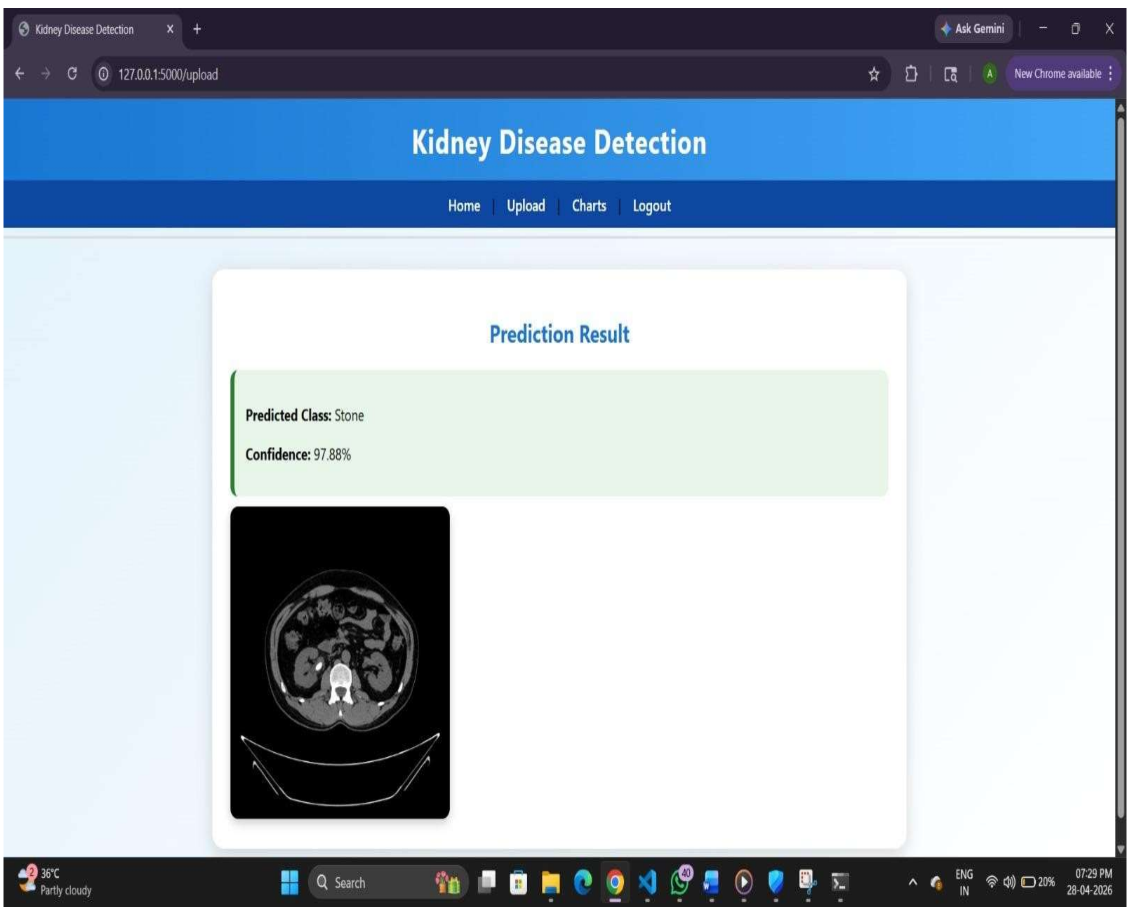
The web application is tested from a user perspective to ensure ease of use, accurate predictions, and proper visualization of results.

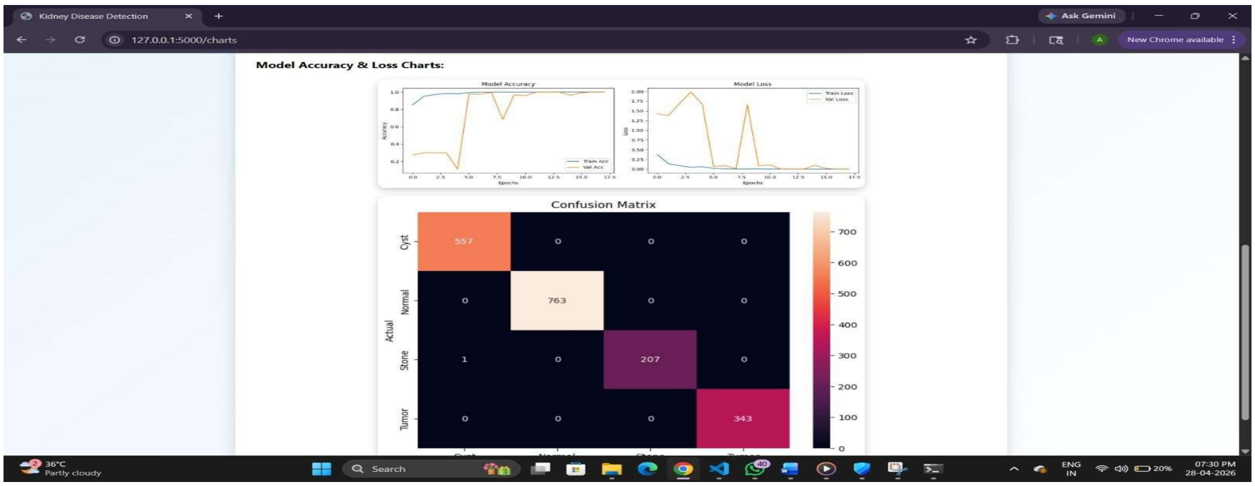
RESULTS

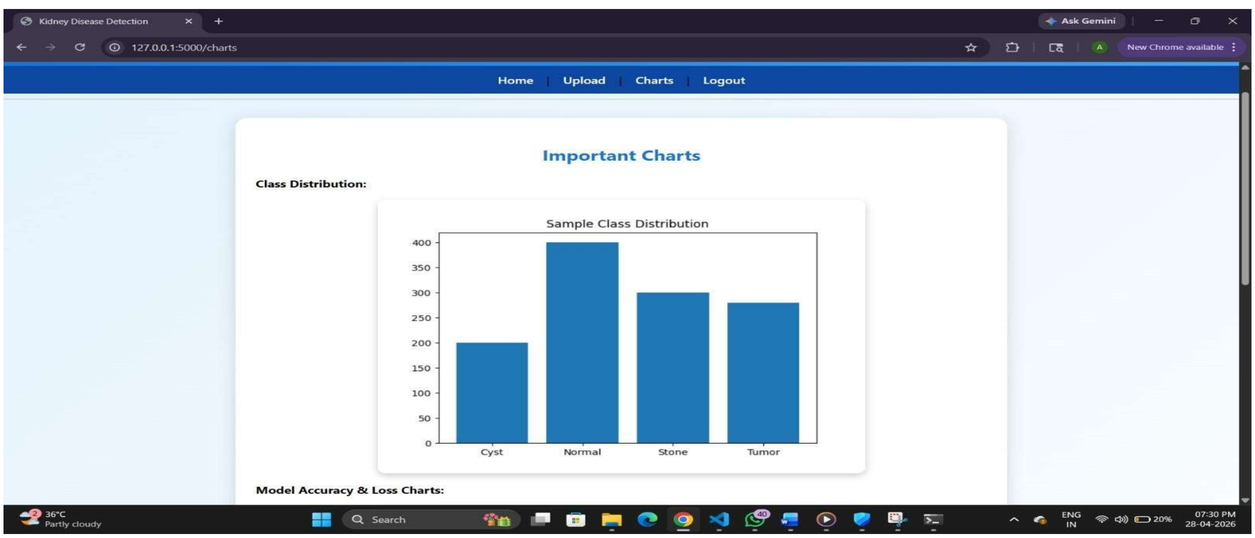
The proposed EfficientNetV2B0-based model achieved an overall accuracy of 95.2% on the kidney CT scan dataset. The model demonstrated high precision, recall, and F1-score across all four classes: Normal, Cyst, Tumor, and Stone.

The confusion matrix indicates minimal misclassification, with slight overlap between cyst and tumor classes. The model showed stable training performance with reduced overfitting. Additionally, the deployed Flask application provided real-time predictions with quick response time, confirming the system's practical usability.









CONCLUSION

In this project, a deep learning–based system was developed for automated detection and classification of kidney diseases from CT scan images. By leveraging the EfficientNetV2B0 architecture with transfer learning, the system effectively classifies images into four categories: Normal, Cyst, Tumor, and Stone, achieving high accuracy and robustness. The integration of data augmentation, class balancing, and fine-tuning techniques ensured strong generalization across diverse CT scans, overcoming limitations of traditional machine learning and earlier CNN models. Furthermore, deployment of the model in a Flask web application provided a practical, user-friendly interface for real-time predictions, visualization, and decision support for radiologists. Overall, this project demonstrates the potential of advanced deep learning models in enhancing kidney disease diagnosis, reducing manual effort, and supporting precision medicine, paving the way for scalable, efficient, and reliable healthcare solutions.

FUTURE SCOPE

The proposed system can be further enhanced by utilizing larger and more diverse datasets to improve model accuracy and generalization. Future work may focus on integrating multi-modal data, including MRI scans and patient clinical records, to enable more comprehensive and reliable diagnosis. The model can also be extended to classify additional kidney disease types and rare tumor conditions, increasing its clinical applicability. Furthermore, deploying the system on cloud or mobile platforms can improve accessibility and support real-time usage in healthcare settings. Incorporating explainable AI techniques will enhance transparency and help medical professionals better interpret the model's predictions.

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