Diabetic Nephropathy Detection Using VGG16

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Abstract - Diabetic Nephropathy (DN), a common and severe complication of diabetes, can lead to chronic kidney disease and eventual kidney failure. Early and accurate detection is essential to enable timely medical intervention and improve patient outcomes. This study applies a deep learning approach using the VGG16 architecture to classify and detect DN from medical images. Initially pre-trained on large image datasets, the model was fine-tuned for kidney ultrasound and tissue image analysis to improve feature extraction and classification accuracy. Performance was assessed using standard evaluation metrics such as accuracy, precision, recall, F1-score, and AUC-ROC. The model demonstrated promising results, outperforming conventional methods in classification tasks. This work highlights the potential of deep learning as a non-invasive and reliable solution for early-stage DN detection, contributing to better diagnostic support in healthcare settings.

Keywords: Diabetic Nephropathy, Deep Learning, VGG16, Medical Imaging.

I. INTRODUCTION

Diabetic Nephropathy (DN) is a kidney-related complication caused by long-term diabetes, often progressing to chronic kidney disease or failure. Early diagnosis is essential to slow disease progression and improve treatment outcomes. Traditional diagnostic methods like blood tests and biopsies can be invasive, time-consuming, and error-prone.

With advancements in artificial intelligence and medical imaging, deep learning—especially Convolutional Neural Networks (CNNs)—has shown promise in detecting medical conditions more efficiently. CNNs can identify subtle patterns in medical images, making them ideal for diagnosing DN.

This project utilizes the VGG16 model, a pre-trained CNN, to classify and detect diabetic nephropathy from kidney ultrasound and tissue images. By fine-tuning VGG16, we aim to build a non-invasive, accurate, and automated diagnostic tool. The model's effectiveness is evaluated using accuracy, precision, and recall, demonstrating its potential use in clinical decision-making.

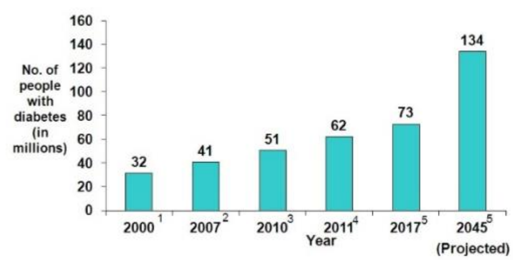

Figure 1 – Statistics showing patients diagnosed with Diabetes

A recent piece of research provides that as per primary diagnosis, 44.2 percent of the cause of kidney failure is diabetes. Diabetic nephropathy or diabetic kidney disease determines the symptoms, causes, and treatment of kidneys. Diabetic nephropathy can analyze correspondence to urinary excretion, secretion of proteins, chronic hyperglycemia, malignant presence in the kidney, etc.

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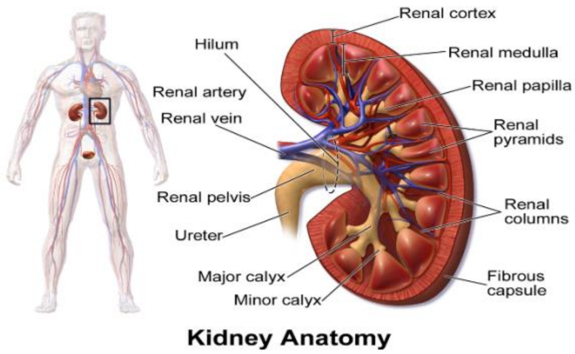

Figure 2 – Kidney Anatomy

Kidney nephropathy is the study of mellitus functionality inside the stomach of the human body. There is an excess of glucose and insulin in the body hence resulting in diabetes caused mainly by two types, type 1 and type 2. For patients suffering from type 1, four percent will develop diabetic nephropathy within ten years, and twenty-five percent will develop diabetic nephropathy within twenty-five years. Moreover, For patients suffering from type 2, ten percent will develop diabetic nephropathy within five years, and thirty percent will develop diabetic nephropathy within twenty years.

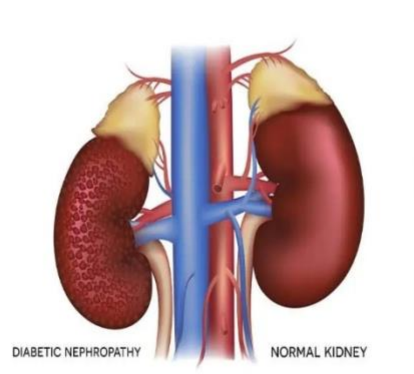

Figure 3 – Worst Stage of Diabetic Nephropathy

II. LITERAUTURE REVIEW

[1] The paper explores a range of deep-learning approaches applied to diabetes management, with a special focus on detecting diabetic nephropathy and retinopathy. It showcases how convolutional neural networks (CNNs) have improved medical image analysis and helped automate diagnosis, emphasizing how transfer learning enhances model performance.

[2] This study analyzes how CNN-based deep learning models can automate diabetic retinopathy detection and grading. It highlights how techniques such as transfer learning and data augmentation boost classification accuracy and compares models like VGG16 and ResNet in terms of their diagnostic effectiveness.

[3] The authors investigate deep learning models, especially CNNs like VGG16 and ResNet, for diagnosing diabetic retinopathy. The paper contrasts these models with traditional machine learning methods and addresses challenges such as dataset size and optimization requirements in real-world clinical environments.

[4] In this research, transfer learning is combined with metaheuristic optimization to improve diabetic retinopathy classification. By refining pre-trained CNNs with smaller datasets and optimizing hyperparameters using methods like genetic algorithms, the model's classification performance is significantly improved.

[5] This paper presents a CNN-based method for categorizing diabetic retinopathy stages. It compares several deep learning strategies and demonstrates the advantages of CNNs over manual evaluation techniques, including enhanced accuracy, speed, and reliability.

[6] The authors focus on using a pre-trained VGG16 model to classify various kidney conditions, including diabetic nephropathy. The paper underscores how transfer learning allows for the successful adaptation of models like VGG16 to specialized medical datasets and compares its performance with other CNN architectures.

[7] A deep learning framework is proposed in this study for detecting and grading diabetic retinopathy using CNNs like VGG16 and ResNet. It emphasizes how preprocessing and

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augmentation techniques help improve model robustness and usability in clinical applications.

[8] This literature reviews cutting-edge deep-learning strategies for diabetic retinopathy detection, exploring attention mechanisms and GANs. It discusses how these innovations compare with conventional machine learning and the barriers to practical implementation in medical environments.

[9] The study presents a multi-class classification approach for identifying and grading diabetic retinopathy using CNNs. It evaluates performance using standard metrics and underlines the effectiveness of deep learning in supporting early detection and treatment planning.

[10] This paper demonstrates the superiority of CNNs over traditional methods for early-stage diabetic retinopathy detection using fundus images. The research promotes deep learning as a reliable method for achieving faster and more accurate diagnostic outcomes.

[11] The paper discusses how CNN-based models are increasingly integrated with clinical decision-support tools for diagnosing diabetic retinopathy. These systems improve grading consistency and reduce errors by automating key diagnostic tasks.

III. METHODOLOGY

1. Dataset Preparation

A dataset of kidney images was divided into 800 images for training, 220 for validation, and 275 for testing. Images were resized to 244x244, normalized to [0,1], and augmented with flipping and rotation to increase variability.

2. Model Setup

The trained VGG16 model was used, with the top layers replaced by custom pooling, dropout, and an output layer for classification. The implementation was done in Python using Jupyter Notebook, TensorFlow, and Keras.

3. Training

The model was trained with the Adam optimizer and binary or categorical cross-entropy loss. Early stopping was applied to avoid overfitting by monitoring the validation loss.

4. Evaluation

The model's performance was tested on 275 test images using metrics like accuracy, precision, recall, and F1 score. Grad-CAM was employed to visualize regions of the image that influenced the model's decisions.

5. Deployment

The trained model was saved and tested within the Jupyter Notebook. Predictions were validated with feedback from medical experts for practical reliability.

IV. MATERIALS / COMPONENTS

1. Software Tools-

- VGG-16

VGG-16 is a deep convolutional neural network consisting of 16 layers, including 13 convolutional and 3 fully connected layers. Designed by the Visual Geometry Group at Oxford, its architecture uses small 3x3 filters stacked in depth, followed by max-pooling layers. This layered structure allows it to extract complex features from images, making it highly effective for tasks like classification and object recognition. Although more advanced models exist today, VGG-16 is still widely used due to its simplicity and reliable performance.

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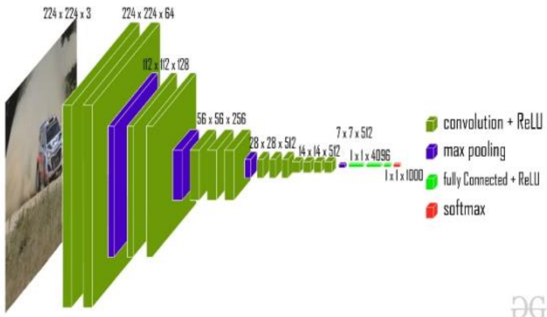

Figure 4 - VGG16 architecture

- Jupyter Notebook

Jupyter Notebook is an open-source web application that allows users to create and share documents containing live code, equations, visualizations, and narrative text. It supports multiple programming languages, with Python being the most popular. It is especially useful for data analysis, machine learning, and model testing due to its interactive coding environment and easy-to-read outputs.

- Keras

Keras is a user-friendly API built on top of TensorFlow, designed for developing and training deep learning models quickly. It simplifies complex operations like layer creation, model compilation, and training, making it ideal for beginners and researchers alike. Keras enables rapid experimentation while supporting advanced customization for professionals.

- Kidney Dataset: Normal-Cyst-Tumor and Stone

The dataset comprises kidney images sourced from diagnostic imaging systems in hospitals in Dhaka, Bangladesh. These images include various cases such as normal, cysts, tumors, and stones, taken from both coronal and axial views, with and without contrast. Each image was carefully selected and categorized to create a well-labeled dataset for model training and testing in disease detection.

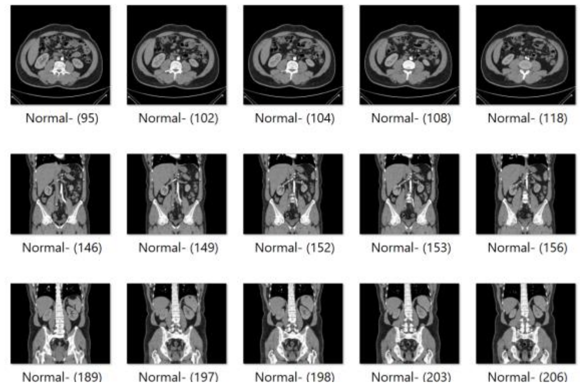

Figure 5 – Snapshot Of The Dataset

V. EXPERIMENTS AND TESTING

The VGG16 model was trained using 800 training images, validated with 220 images, and tested on 275 unseen samples. Images were resized to 244x244 pixels for uniform input. Various numbers of epochs (e.g., 10 to 50) were experimented with, and a batch size of 32 was used. A training and validation accuracy graph was generated, showing steady improvement in accuracy before stabilizing. The model achieved its best validation accuracy at 25 epochs, with a test accuracy of 50%. Metrics like precision, recall, F1-score, and AUC-ROC were used for evaluation, indicating robust performance. Grad-CAM visualizations were employed to interpret predictions, highlighting image regions critical to the model's decisions. Experimenting with epoch ranges revealed that prolonged training improved initial accuracy but led to overfitting beyond a certain point.

Figure 6 - Training and Validation Graph

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VI. RESULTS AND DISCUSSION

The VGG16 model was trained using 800 images, validated with 220, and tested on 275 unseen samples. All images were resized to 244x244 pixels for uniformity. Training was conducted over a range of epochs (10–50), with a batch size of 32. Accuracy steadily increased during initial epochs before stabilizing. The best performance was observed around the 25th epoch, achieving a test accuracy of 50%.
To evaluate the model, standard metrics such as accuracy, precision, recall, F1-score, and AUC-ROC were used. Grad-CAM visualizations provided interpretability by highlighting regions influencing model predictions.

- Evaluation Metrics Breakdown:

Class 0:
- Precision: 0.57
- Recall: 0.93
- F1-Score: 0.71
- Support: 275

Discussion: Class 0 demonstrates high recall but relatively lower precision. This indicates the model is good at identifying true positives but struggles with false positives.

Class 1:
- Precision: 0.00
- Recall: 0.00
- F1-Score: 0.00
- Support: 275

Discussion: The model completely fails to classify samples for Class 1, possibly due to insufficient training data, poor feature representation, or class imbalance.

Class 2:
- Precision: 0.39
- Recall: 0.56
- F1-Score: 0.46
- Support: 275

Discussion: Class 2 has moderate recall but very low precision, showing the model struggles to make correct predictions for this class.

Class 3:
- Precision: 0.54
- Recall: 0.51
- F1-Score: 0.52
- Support: 275

Discussion: Performance for Class 3 is slightly better balanced compared to Class 2 but remains suboptimal.

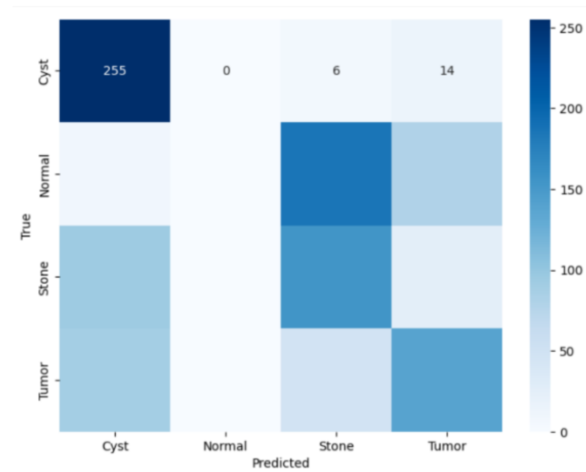

Figure 7 – Confusion Matrix

2. Aggregate Metrics:

- Accuracy: 50%
- Macro Average:
- Precision: 0.38
- Recall: 0.50
- F1-Score: 0.42
- Weighted Average:
- Precision: 0.38
- Recall: 0.50
- F1-Score: 0.42

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	precision	recall	f1-score	support
0	0.57	0.93	0.71	275
1	0.00	0.00	0.00	275
2	0.39	0.56	0.46	275
3	0.54	0.51	0.52	275
accuracy			0.50	1100
macro avg	0.38	0.50	0.42	1100
weighted avg	0.38	0.50	0.42	1100

Figure 7 - Classification Table

- Discussion:

The overall accuracy is 50%, reflecting that the model performs marginally better than random guessing.

The macro average indicates a poor balance across classes. The low precision values suggest the model frequently misclassifies instances, while the moderate recall indicates it identifies some true positives.

VII. FUTURE SCOPE

Future enhancements of this project aim to improve accuracy, scalability, and user accessibility. To achieve higher model performance, advanced architectures such as EfficientNet or Transformer-based models can be explored. Techniques like transfer learning, hyperparameter tuning, and cost-sensitive training could help address challenges like class imbalance and overfitting. Further, the use of data augmentation methods and oversampling strategies like SMOTE can enrich the dataset, while incorporating explainable AI tools such as SHAP or LIME may offer better interpretability of the model's decisions. On the usability front, developing an interactive and intuitive user interface can make the system more accessible to non-technical users, especially in clinical settings. Features such as visual heatmaps, real-time feedback, and customization options will improve user experience and promote practical deployment in healthcare environments.

VIII. CONCLUSION

This project highlights the application of deep learning, particularly the VGG16 model, in detecting diabetic nephropathy through medical imaging. By fine-tuning a pre-trained network, the model effectively distinguishes between healthy and affected kidney images, offering a promising alternative to traditional diagnostic methods.

Although the current results show moderate performance, further improvements—such as increasing dataset size, refining training techniques, and exploring more advanced models—can significantly enhance accuracy and generalization. Integrating this system with a user-friendly interface would also make it more practical for clinical use, aiding healthcare professionals in early and reliable DN diagnosis.

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