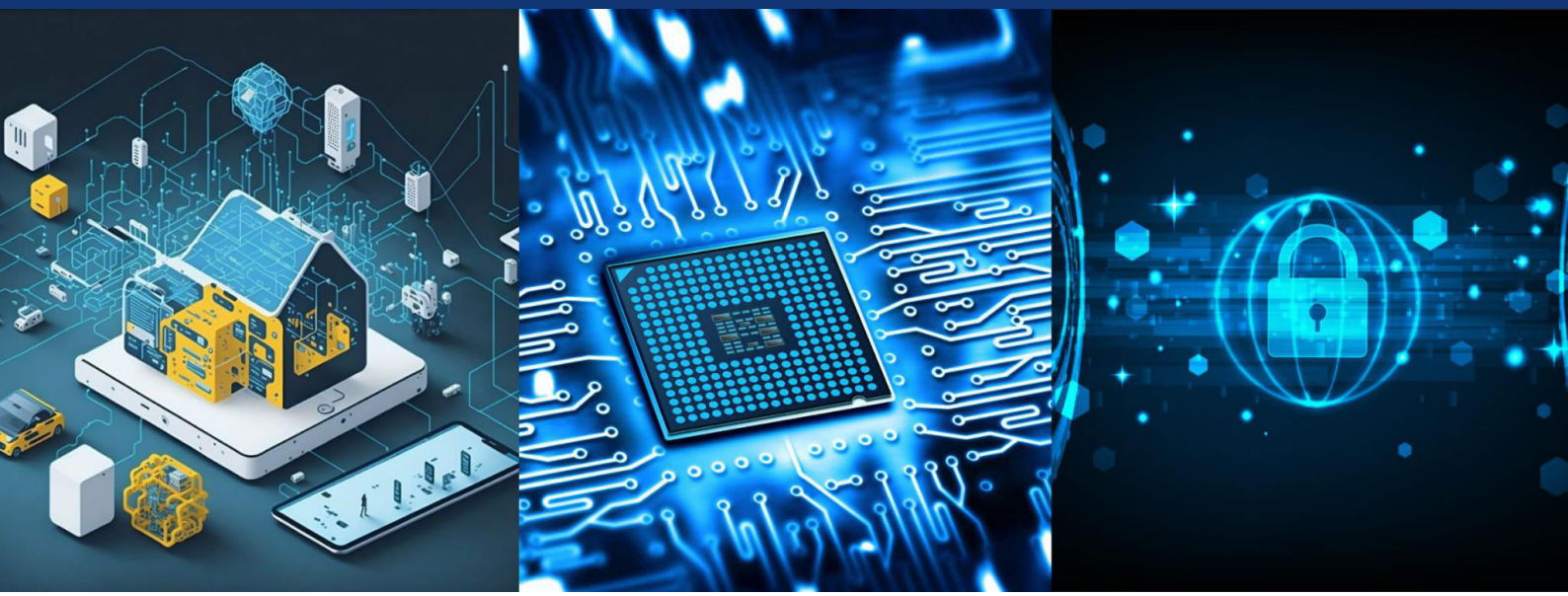
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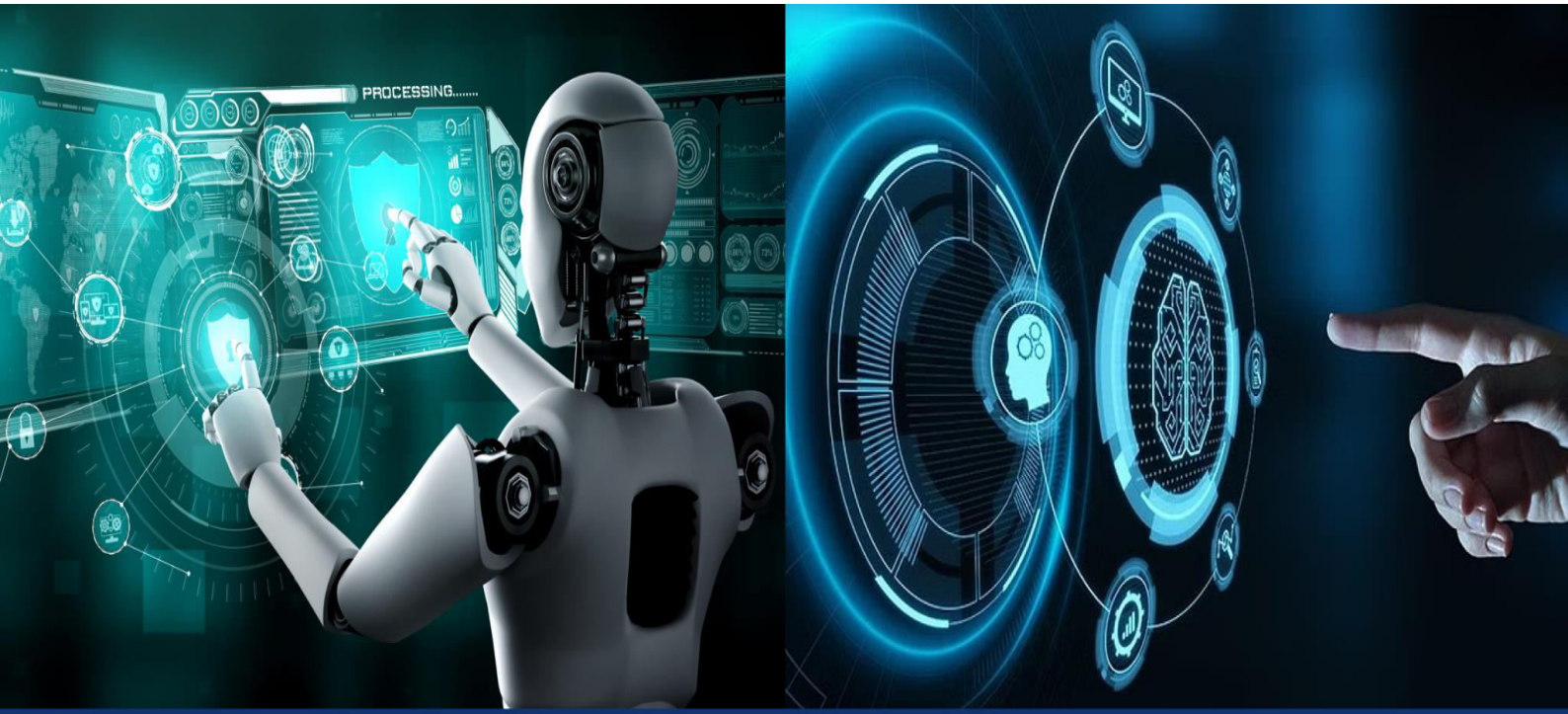
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Predictive Modeling of Chronic Kidney Disease Using Deep Learning

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ABSTRACT: Chronic kidney disease (CKD) tends to progress silently, and many patients reach an advanced stage before it is noticed. This paper presents a deep learning system that screens kidney images and turns the outcome into something a patient can act on. A ResNet9 convolutional network was trained on preprocessed kidney images and reached 98.88% accuracy on the validation set and 98.036% on the held-out test set. The trained model is deployed through a Flask web application that returns the predicted class with a confidence score, generates a downloadable PDF report, and lists diet and lifestyle suggestions. The whole pipeline runs on an ordinary Intel Core i5 machine with 8 GB of RAM, so it does not depend on specialised hardware. Our results suggest that a compact residual network, combined with a simple reporting layer, can serve as a practical decision-support tool for early CKD screening.

KEYWORD: Chronic kidney disease, deep learning, ResNet9, convolutional neural network, medical image classification, clinical decision support.

I. INTRODUCTION

The kidneys do a lot of quiet work. They clear waste from the blood, keep fluid and electrolyte levels balanced and help hold blood pressure steady. In chronic kidney disease (CKD) this capacity wears away slowly, sometimes over many years, and since the early stages cause few or no symptoms, a large share of patients are diagnosed only after serious damage has been done [1]. At that point the choices narrow to dialysis or a transplant, both expensive and hard to reach in many regions.

Routine diagnosis rests on blood and urine tests, a clinical examination and imaging that a trained specialist has to interpret. These steps are dependable, but they take time, they need experienced staff and they are not always available in smaller clinics. Deep learning has reshaped medical image analysis over the last decade [2], and convolutional neural networks (CNNs) in particular can pick up fine texture and shape cues that are easy to miss by eye.

In this paper we describe a CKD screening system built around a ResNet9 image classifier. The model reads a kidney image, predicts its class together with a confidence score, and passes the outcome to a web application that goes one step further than a bare label: it assembles a downloadable PDF report and a short set of diet and lifestyle suggestions. We wanted something a clinician could use for a quick second look and a patient could actually understand. The main contributions are:

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- a compact ResNet9 classifier for kidney images that reaches 98.88% validation accuracy and 98.036% test accuracy;
- an end-to-end pipeline covering preprocessing, prediction, report generation and guidance in a single web interface;
- a lightweight implementation that runs on ordinary hardware (Intel Core i5, 8 GB RAM), which keeps the barrier to adoption low.

The rest of the paper is organised as follows. Section 2 reviews related work, Section 3 explains the methodology, Section 4 lists the implementation environment, Section 5 presents the results, and Sections 6 and 7 discuss limitations and conclude.

II. RELATED WORK

Image-based kidney analysis has mostly been studied on ultrasound, because the modality is cheap and widely available. Sudharson and Kokil combined several pretrained networks through transfer learning to separate normal, cyst, stone and tumour ultrasound images, and report a best accuracy of 96.54% on good-quality images and 95.58% on noisy ones [6]. George and Anita applied Gaussian filtering and contrast-limited histogram equalisation before feature extraction, and found that ResNet-50 features paired with an SVM classifier worked best among the options they compared [7]. Molina-Moreno et al. went in a different direction with URI-CADS, a multi-task network that segments the kidney and flags several pathologies on a public set of 1985 ultrasound images; their AUC was 87.41% for healthy-versus-pathological diagnosis, which reflects how hard a wide taxonomy of findings is [8].

Looking across these studies, three gaps stand out to us. First, much of the literature stops at the classifier and does not describe how a prediction would reach a doctor or a patient. Second, heavy backbones and ensembles raise the compute cost, which matters for low-resource settings. Third, little attention is paid to turning a prediction into plain-language guidance. Our work addresses these points by pairing a small residual network [3, 4] with a simple web front end and an automatic report.

III. PROPOSED METHODOLOGY

3.1 System Overview

Fig. 1 shows how the pieces fit together. A user uploads a kidney image through the browser. The image is cleaned and resized, passed to the ResNet9 model running behind a Flask server, and the predicted class and confidence are stored in a database together with the image. The report module then builds a PDF and the matching lifestyle advice, and both are returned to the user.

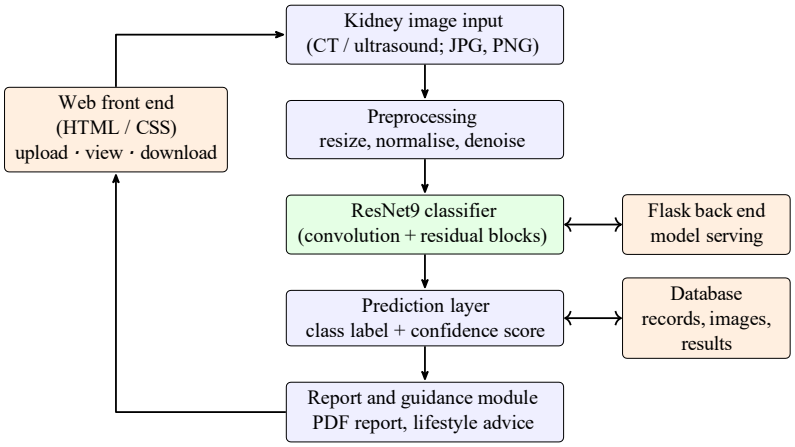


Fig - 1: Overall architecture of the proposed CKD screening system.

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3.2 Dataset and Preprocessing

Our training material is a collection of kidney images spread over [number of classes] classes, [total images] images altogether. We split them into train, validation and test portions using a [split ratio] ratio, and nothing from the test portion was touched until the very last evaluation. Before an image reaches the network we apply three steps: resizing to a fixed [image size]×[image size] resolution, scaling pixel values to a common range, and a light denoising filter to suppress scanner noise. Resizing and rescaling are applied identically at training and prediction time so the deployed model sees the same kind of input it was trained on.

3.3 ResNet9 Classifier

We chose ResNet9 because it keeps the main idea of residual learning [3] while staying small enough to train on a modest machine. The layout is shown in Fig. 2. A stem of two convolution layers is followed by a first residual block, then two further convolution stages that widen the feature maps to 512 channels, a second residual block, global pooling and a fully connected layer with a softmax output. Each convolution is followed by batch normalisation [5] and a ReLU activation. The skip connections let gradients flow directly through the block, which makes optimisation easier than in a plain stack of the same depth. The configuration follows the widely used ResNet9 recipe popularised for fast training [4].

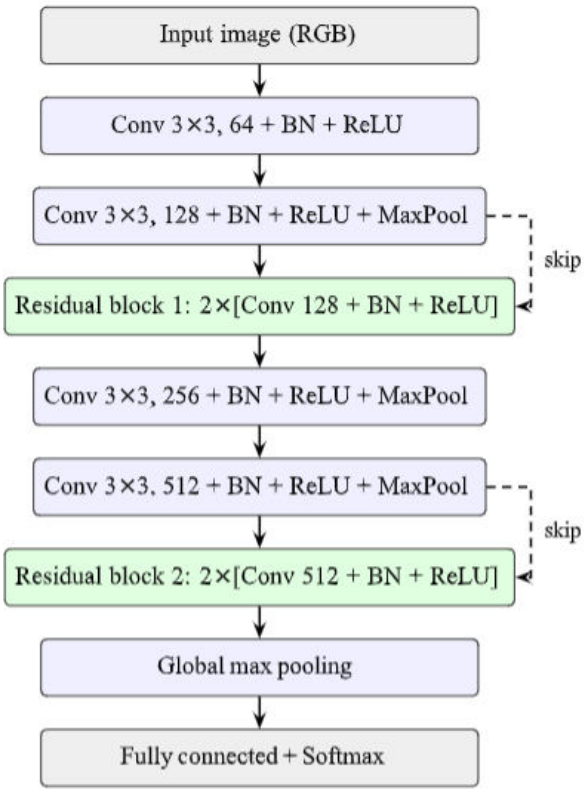


Fig - 2: ResNet9 layout used for classification. Dashed arrows show the skip connections of the two residual blocks (green).

3.4 Training Setup

The network was trained end to end with a softmax output and a cross-entropy loss. Table 1 collects the training settings. We picked the checkpoint with the best validation accuracy and then ran it a single time on the untouched test portion.

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Table - 1: Training configuration of the ResNet9 model

Setting	Value
Architecture	ResNet9 (2 residual blocks)
Input size	[image size]×[image size]×3
Optimiser	[optimiser]
Learning rate	[learning rate]
Batch size	[batch size]
Epochs	[epochs]
Loss function	Categorical cross-entropy
Framework	TensorFlow / Keras

3.5 Application Layer and Report Generation

The trained model is wrapped in a Flask service with an HTML/CSS front end. Fig. 3 follows one request from start to finish. If the model flags an abnormality, the report module produces a PDF with the patient details and the predicted finding, and attaches diet and lifestyle suggestions tied to that finding. If nothing abnormal is found, the user sees a healthy-status message with general precautions. In both cases the result page also carries a disclaimer reminding the reader that the output is a screening aid and not a diagnosis.

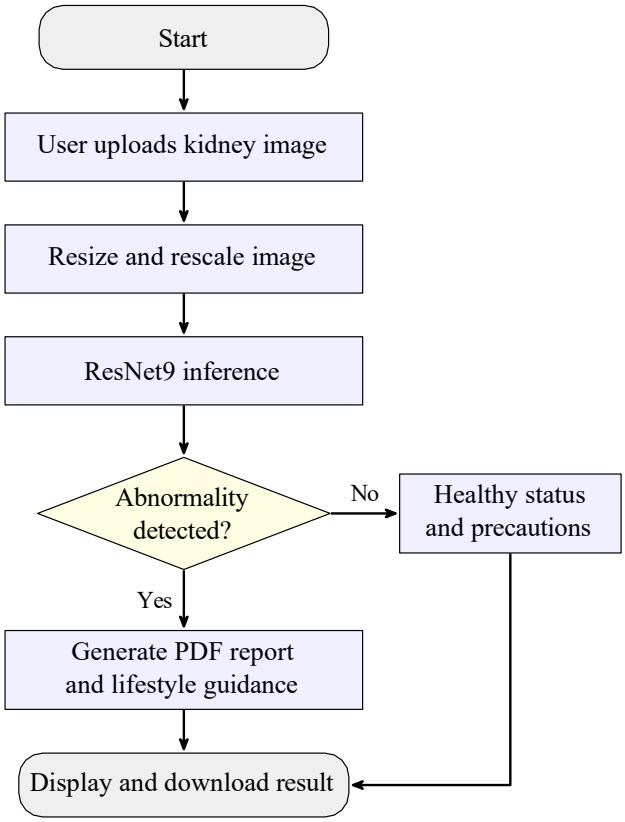


Fig - 3: Working flow of the application, from image upload to the downloadable report.

IV. IMPLEMENTATION ENVIRONMENT

Everything was developed and tested on a standard laptop-class machine, which was deliberate: we wanted to show that the pipeline does not depend on specialised hardware. Table 2 lists the tools used.

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Table - 2: Hardware and software environment

Component	Specification
Processor	Intel Core i5
Memory	8 GB RAM
Storage	512 GB SSD
Language	Python
Deep learning	TensorFlow / Keras
Data handling	Scikit-learn, Pandas, NumPy
Web stack	Flask, HTML, CSS
Development	Jupyter Notebook

V. RESULTS AND DISCUSSION

5.1 Classification Performance

On the validation set the model reached 98.88% accuracy, and on the unseen test set it reached 98.036%. The gap between the two is under one percentage point (0.84), which suggests the network is not simply memorising the training images. Table 3 and Fig. 4 summarise these numbers.

Table - 3: Performance of the ResNet9 model

Data split	Accuracy (%)
Validation	98.88
Test	98.036

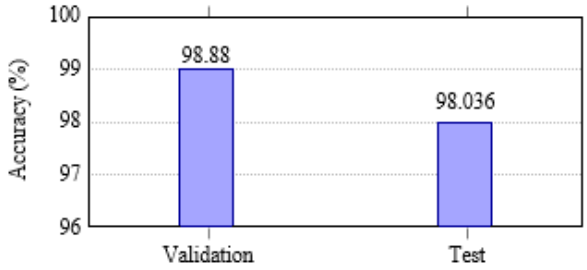


Fig - 4: Validation and test accuracy of the ResNet9 model (vertical axis starts at 96% to make the small gap visible).

5.2 Comparison with Earlier Studies

Table 4 places our result next to the studies discussed in Section 2. The comparison is only indicative: the datasets, imaging modalities, class definitions and metrics differ from paper to paper, so the numbers should not be read as a head-to-head ranking.

Table - 4: Rough comparison against earlier studies

Study	Modality	Method	Reported
[6]	Ultrasound	Ensemble of DNNs	96.54% acc.
[7]	Ultrasound	ResNet-50 features + SVM	Best of the methods compared
[8]	Ultrasound	Multi-task CNN	87.41% AUC
Ours	Kidney images	ResNet9 (residual CNN)	98.036% acc.

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5.3 Application Output

The web interface has three screens plus a result page. The home page, shown in Fig. 5, introduces the system and gives access to the other screens through a side menu.



Fig - 5: Home page of the CKD detection web application.

The about page (Fig. 6) gives short background material on CKD and deep learning, so that a first-time visitor understands what the tool is doing.

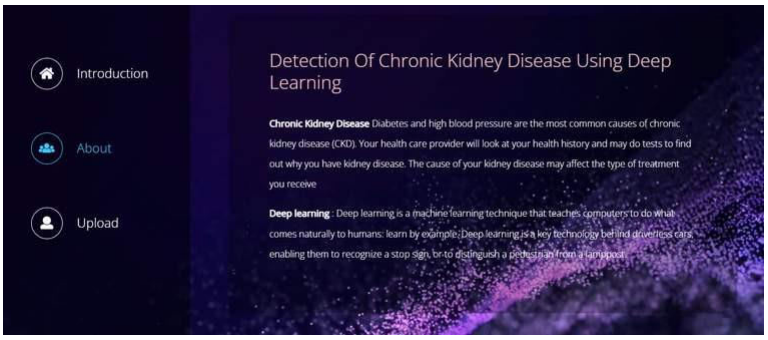


Fig - 6: About page with background on chronic kidney disease and deep learning.

On the upload page (Fig. 7) the user picks a kidney image and a model and then submits the form.

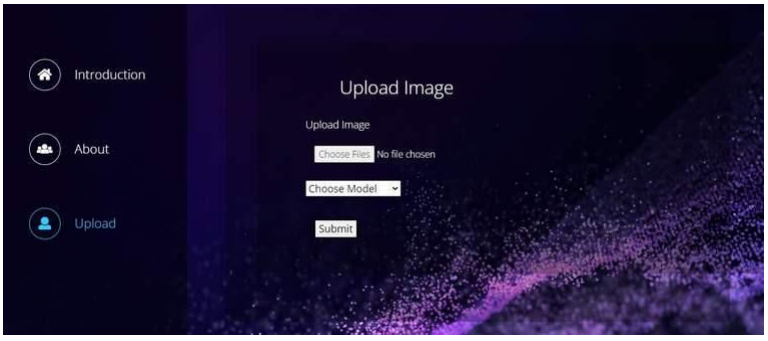


Fig - 7: Upload page for selecting a kidney image and a model.

After a prediction is made, the result page (Fig. 8) displays the predicted class along with a confidence score, and below that come treatment guidance and a short list of lifestyle suggestions. In the sample shown, the model labels the image as a cyst with a confidence of 98.036%, and the page points out that simple cysts are usually benign and that a urologist should be consulted if a cyst is large or painful.

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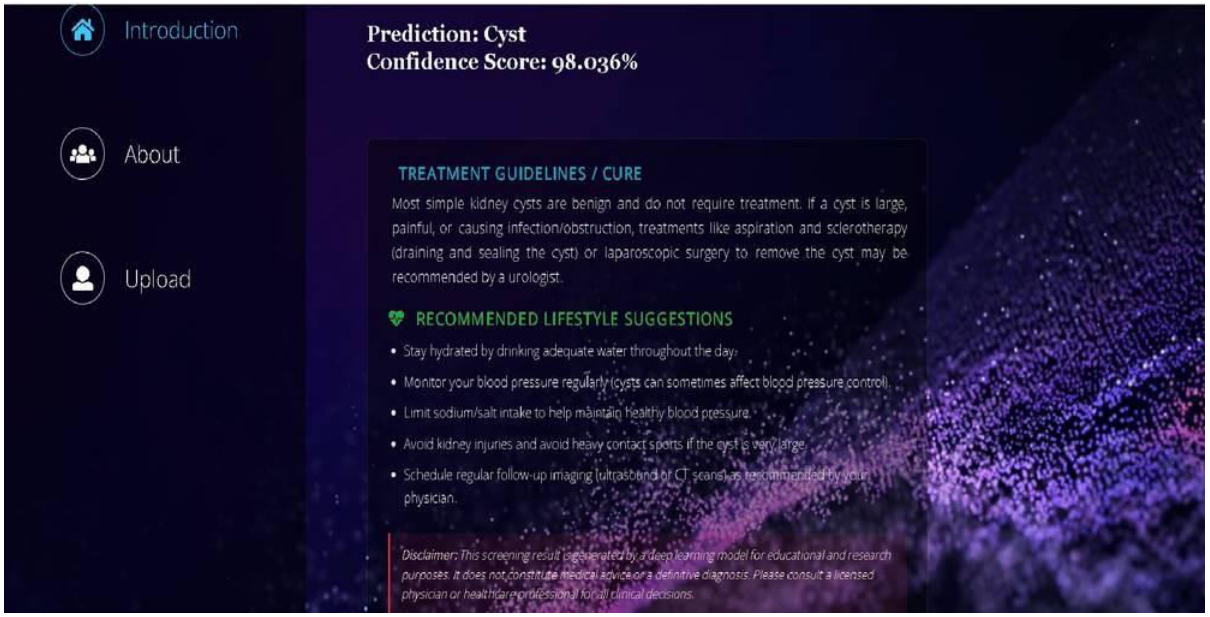


Fig - 8: Result page showing the predicted class, confidence score, treatment guidance and lifestyle suggestions.

VI. LIMITATIONS AND FUTURE WORK

We want to be upfront about what this study does and does not show. The results come from a single dataset and a single train/validation/test division, so they tell us little about how the model would behave on images from other scanners or hospitals; external validation is the obvious next step. The confidence score shown to users is the softmax output, which is not automatically a calibrated probability. Finally, the system is a screening aid and the lifestyle text is general guidance, so neither replaces a clinician's judgement.

In future work we plan to add clinical and laboratory values next to the image, so that the system can estimate the CKD stage rather than only the image class. We also want to test explainability tools such as Grad-CAM, evaluate the model on data from additional centres, and consider a mobile front end for clinics with limited connectivity.

VII. CONCLUSION

This paper presented a ResNet9-based system for kidney image screening that is packaged as a complete web application. The model achieved 98.88% validation accuracy and 98.036% test accuracy, and the application turns each prediction into a PDF report and plain-language lifestyle guidance. Because it runs on ordinary hardware, the approach could be useful where specialist time and computing resources are scarce. Broader validation and richer clinical inputs are the main steps needed before it could support real-world decisions.

VIII. ACKNOWLEDGMENT

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