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AI-Based Kidney Stone Detection Using Ultrasound Imaging

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Abstract: ***Kidney stone disease is a common urological condition where delayed detection can lead to severe complications. Diagnosis using ultrasound imaging depends on expert interpretation, which may not always be available in resource-limited settings. Manual analysis is time-consuming and pronetovariability,reducingthereliabilityofearly screening. Although artificial intelligence has shownpotentialinmedicalimaging,manyexisting systems lack robustness in handling irrelevant inputs. To address this, this work presents an AI-based kidney stone detection system using ultrasound imaging. The framework utilizes a MobileNetV2-based convolutional neural network with transfer learning to classify images into Normal and Kidney Stone Detected categories. A deep feature-based validation mechanism ensures that only relevant kidney ultrasound images are processed, preventing incorrect predictions. Grad-CAMvisualizationsareusedtohighlightimportant regions influencing the model's decision.***

Experimental results demonstrate that the system provides accurate and reliable predictions. The model is deployed as a Flask-based web application, enabling real-time analysis with confidence scores and visual explanations. This work highlights the effectiveness of combining deep learning and explainable AI for kidney stone screening.

Keywords: Kidney stone detection, ultrasound imaging, MobileNetV2, deep learning, transfer learning, Grad-CAM, explainable AI, medical image analysis, Flask, clinical decision support.

I. INTRODUCTION

Kidney stone disease is a common urological disorder that can lead to severe pain and complications if not detected early. Accurate and timelydiagnosisisessentialforeffectivetreatment. Ultrasound imaging is widely used due to its non-invasive nature and affordability; however, its interpretation requires expert knowledge and is often subject to variability. In resource-limited settings, the lack of specialists further delays diagnosis, highlighting the need for automated detection systems. With the growth of medical imaging and artificial intelligence, deep learning techniques have been increasingly applied to support kidney stone detection. This project is implemented in Python using a modular architecture to ensure scalability, maintainability, and efficiency in medical image analysis.

Deep learning models, particularly Convolutional Neural Networks (CNNs), have shown strong performance in medical image classification. A study by [1] Valarmathi et al. (2023) utilized preprocessingandCNN-basedclassificationonCT images, achieving improved accuracy over traditional methods. However, the approach relies heavily on CT imaging and extensive preprocessing, limiting its use in low-resource environments.

Similarly, [2] Mangala Shetty et al. (2024) proposed a CNN-based model for kidney stone detection using CT and ultrasound images, achievingapproximately97%accuracy.Despiteits high performance, the model lacks an image validationmechanism,makingitpronetoincorrect predictions when irrelevant inputs are provided.

Furthermore,[3]Kumaretal.(2024)explored transfer learning models such as MobileNet and DenseNet for kidney disease detection on CT datasets. Their work demonstrated competitive accuracy with reduced computational cost, but it mainlyfocusedonCT imaginganddidnotaddress ultrasound-based detection.

Motivated by these limitations, the proposed system uses a MobileNetV2-based deep learning modelwith arobustvalidation mechanismtoensure reliable kidney stone detection from ultrasound images. The system is evaluated using standard metrics such as accuracy, precision, recall, and confusion matrix analysis to ensure reliable performance.

II. LITERATURE SURVEY

Recent studies indicate that traditional image processing and rule-based approaches are inadequate for kidney stone detection due to complex texture patterns in ultrasound images and variability in imaging conditions.

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Consequently, machine learning (ML) and deep learning (DL) techniques have gained significant attention for improving detection accuracy and reliability.

[4] Al-Tbenawey et al. (2023) conducted a comparativestudybetweenKNNandCNNmodels for kidney stone detection using imaging data. Their results showed that CNN significantly outperformed traditional ML methods in accuracy and robustness. However, the implementation was limited to a MATLAB-based environment and lacked real-time deployment capabilities. [5] George&Anita(2022)proposedahybridapproach combining Gaussian filtering, CLAHE enhancement, CNN feature extraction, and SVM classification on ultrasound images. While the system achieved high accuracy in detecting stones andcysts,themulti-stagepipelineincreasedsystem complexityandprocessingtime.[6]SabithaRaniet al.(2023)utilizedwatershedsegmentation,GLCM feature extraction, and Probabilistic Neural Networks for kidney stone detection. The model achieved an accuracy of approximately 86.8%, but its performance was lower compared to modern CNN-basedtransferlearningapproaches.[7]Tejbir Singh et al. (2024) developed an ultrasound-based technique using image segmentation and radial transformforstonelocalizationandsizeestimation. Altho ugheffectiveinidentifyingstonelocation,the reliance on handcrafted features reduced adaptability to diverse imaging conditions. [8] Karthikeyan et al. (2024) explored deep CNN architectures such as VGG16, ResNet, and DenseNetonCTdatasets,achievingaccuracyupto 99%. Despite high performance, these models required high computational resources and longer training times. [9] Shoayee Alotaibi proposed a kernel-based machine learning approach using Kernel-ELM with level-set segmentation on ultrasound images, achieving moderate accuracy; however, traditional ML techniques struggled with complextexturevariationsin medical images. [10] Zahida Mir introduced YOLOv8 and YOLOv9 models for real-time kidney stone detection on CT images, achieving high-speed and accurate localization. However, the approach required bounding-boxannotationsandfocusedprimarilyon detectionratherthanclassification.[11]SpoorthiB. Shetty conducted a comprehensive survey on kidneystonedetectiontechniques,highlightingthe advantages of deep learning methods while identifying challenges such as noise, limited datasets,andvariabilityinimagingconditions.[12] Muhammed Altaf performed a comparative analysis of CNN and hybrid ML–DL models, concluding that transfer learning approaches consistently outperform traditional ML methods, although performance heavily depends on dataset quality. [13] Noshi proposed a web-based deep learning system using CNN models deployed through Flask for real-time kidney stone detection. While the system improved accessibility and usability,itrequiredstrictinputvalidationtoavoid incorrect predictions. [14] Challapanati Vamsikrishna introduced an ultrasound-based detection framework with preprocessing and domainvalidationmechanisms,whichsuccessfully reduced misclassification of non-kidney images. However, the validation process increased system complexity. [15] Eswar S. explored ensemble and transfer learning approaches for kidney stone classification, achieving improved robustness and reduced overfitting, though at the cost ofincreased computational complexity and training overhead.

III. PROPOSED METHODOLOGY

This study aims to address the identified research gap by developing a deep learning–based framework for accurate and reliable kidney stone detection using ultrasound imaging. Kidney stone diseaseisasignificanturologicalconditionthatcan lead to severe pain, infections, and long-term complications if not diagnosed early. Early detectionisessentialtoensuretimelytreatmentand reducehealthcarerisks.However,ultrasoundimage interpretation depends heavily on expert radiologists and is often affected by noise, low contrast,andoperatorvariability.Thesechallenges highlight the need for an automated, robust, and interpretable detection system.

Traditional image processing and rule-based approacheshavebeenwidelyusedforkidneystone detection; however, they struggle to capture complextexturepatternsandarehighlysensitiveto noise and imaging variations. Classical machine learning techniques improved detection performance but depend heavily on handcrafted features and lack generalization across diverse datasets. More recent deep learning approaches, particularly Convolutional Neural Networks (CNNs) and transfer learning models, have demonstrated superior performance by automatically learning spatial features from medical images. However, many existing systems lackinputvalidationmechanismsandmayproduce incorrect predictions when irrelevant or non-medical images are provided, reducing system reliability.

To overcome these limitations, the proposed KidneyAI system utilizes a MobileNetV2-based deeplearningmodelcombinedwitharobustimage validation mechanism and explainable AI techniques.Thesystem followsamodularpipeline starting from data collection and preprocessing, where kidney ultrasound images are standardized and prepared for model training. A transfer learning–based CNN model is used to classify images into Normal and Kidney Stone Detected categories.Adeepfeature-basedvalidationmodule ensuresthatonlyrelevantkidneyultrasoundimages are processed, improving system reliability. Additionally,Grad-CAMvisualizationisemployed tohighlightimportantregionsinfluencingthe model's decision, enhancing interpretability and trust.

Furthermore,theproposedsystememphasizesreal-time usability and accessibility through a lightweight web-based deployment. By integrating thetrainedmodelintoaFlaskapplication,userscan upload ultrasound images and receive instant predictionsalongwithconfidencescoresandvisual explanations. The inclusion of an input validation layer ensures that the system maintains robustness by rejecting invalid or non-medical images before analysis. This design not only enhances system reliability but also makes the solution practical for academic demonstrations and potential healthcare support applications.

The methodology consists of the following stages:

- Step1–LiteratureReviewandProblemDefinition: Analyze existing kidney stone detectionmethods, identify limitationssuchaslack of validationandhighcomputationalcomplexity, anddefinetheneed forarobustandexplainableAI-based system.
- Step 2 – Data Collection: Collect kidney ultrasound image datasets from reliable sources, including both normal and kidney stone cases.
- Step 3 – Preprocessing: Perform image resizing, normalization, RGB conversion, and data augmentation techniques such as rotation and zooming to improve model generalization.
- Step4–ModelDevelopment:Implementa transferlearning–basedMobileNetV2modelfor binary classification of kidney ultrasound images. Step5–Training:Trainthemodelusingoptimizedparametersandregularizationtechniques to improve accuracy and prevent overfitting.
- Step6–Evaluation:Evaluatemodelperformance using metrics such as accuracy, precision, recall, and confusion matrix analysis.
- Step 7 – Validation and Visualization: Apply image validation to filter irrelevant inputs and generate Grad-CAM heatmaps to visualize regions influencing predictions.
- Step8–DeploymentandConclusion:Deploythe model as a Flask-based web application, demonstrate real-time predictions with confidence scores, and analyze system performance for practical applications.

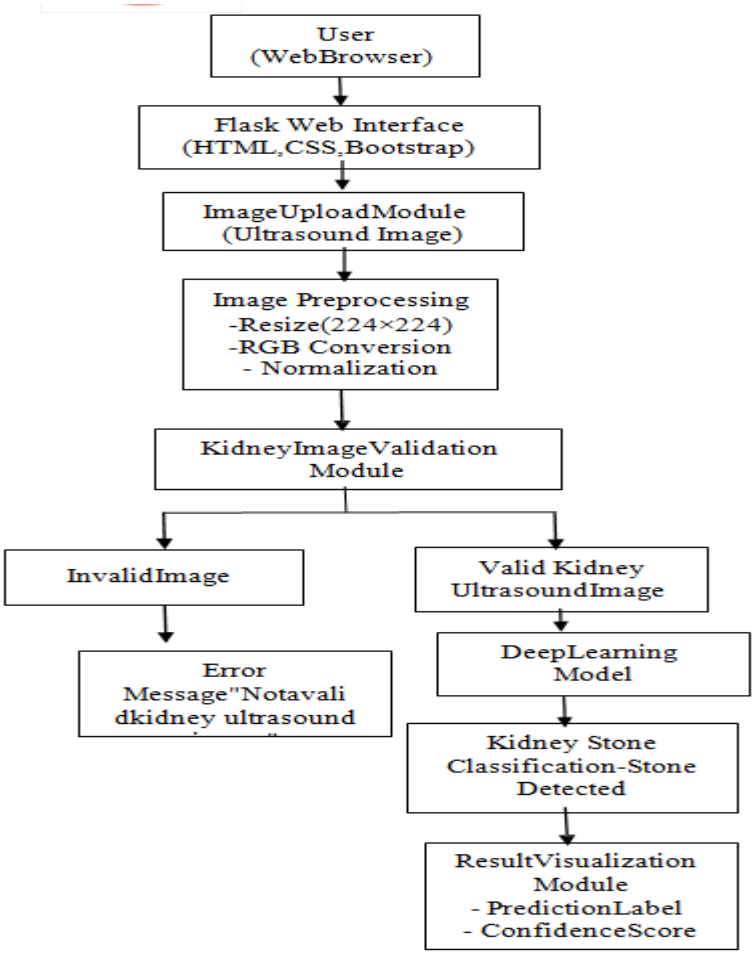


Figure1: SystemArchitecture

Thefigureillustratesthe overall architectureofthe proposed KidneyAI system for kidney stone detection using ultrasound imaging. The workflow begins with the user interacting through a web browser, where a Flask-based web interface built using HTML, CSS, and Bootstrap provides an accessible platform for image upload and result visualization.

Once an ultrasound image is uploaded through the Image Upload Module, it is forwarded to the image preprocessing stage, where essential transformationsareapplied.Theseincluderesizing the image to 224×224 pixels, converting it into RGBformat,andnormalizingpixelvaluestoensurecompatibilitywiththedeeplearningmodel.

Followingpreprocessing,theimageispassedtothe Kidney Image Validation Module, which performsdeepfeaturecomparisontoverifywhether the input image belongs to the kidney ultrasound domain. If the image is identified as invalid or unrelated, the system immediately generates an error message stating that it is not a valid kidney ultrasound image, thereby preventing incorrect predictions.

Iftheimagepassesvalidation,itisforwardedtothe deep learning model based on MobileNetV2 CNN architecture. The model performs binary classification to determine whether a kidney stone ispresentornot.Theoutputiscategorizedintotwo classes: *Stone Detected* or *No Stone Detected.*

Finally,theresultsaredisplayedthroughtheResult Visualization Module, which presents the predictionlabel,confidencescore,andapreviewof the uploaded image. This structured pipeline ensures reliable, accurate, and interpretable detection while maintaining system robustness through input validation and real-time processing.

A. Model Configurations

1) Deep Learning-Based Kidney Stone Detection Model

A transfer learning–based Convolutional Neural Network (CNN) is implemented for kidney stone detection using ultrasound images. The model is developed using TensorFlow/Keras with a pretrained MobileNetV2 backbone, fine-tuned for binary medical image classification. The model is trained on kidney ultrasound images categorized into normal and stone-affected classes.

- Input:Preprocessedultrasoundimagesresized to 224×224 pixels.
- Architecture: Pretrained MobileNetV2 backbonewithcustomfullyconnectedlayers.
- Outputclasses:Normal,KidneyStone Detected.
- Lossfunction:Binarycross-entropy.
- Optimizer:Adam.
- Regularization: Data augmentation and dropoutlayerstoimprovegeneralization.
- Savedmodel:model_kidney.h5.

Toimprovemodelinterpretability,Grad-CAMis appliedto generate heatmap visualizations highlighting the regions influencing the model's predictions.

ImageValidationModel(OODDetection)To ensure system reliability, an image validation mechanism is incorporated to verify whether the uploaded input belongs to the kidney ultrasound domain before classification. This module uses deepfeatureextractionandstatisticalcomparisonto detect out-of-distribution (OOD) inputs.

- Input:Preprocessedimagefeaturesextracted using a pretrained feature extractor.
- Method:Featuredistancecomparisonwith reference kidney image embeddings.
- Output:ValidKidneyImage/ Invalid Image.
- Thresholding:Distance-basedthresholdto reject non-kidney images.
- Purpose:Preventincorrectpredictionson irrelevant or non-medical images.

This validation model acts as a safety layer, ensuring that only relevant medical images are processed by the classification model.

B. Training Procedure

The training process for the deep learning model follows a structured pipeline:

- Initialization oftheMobileNetV2-based model architecture.
- Compilation using binary cross-entropy loss and Adam optimizer.
- Training over multiple epochs with batch-wise updates.
- Application of regularization techniques such as data augmentation, dropout, and early stopping to prevent overfitting.
- Saving the best-performing model weights based on validation performance.

C. EvaluationMetrics

The performance of the proposed model is evaluated using standard classification metrics to ensure reliability:

- Accuracy
- Precision
- Recall
- F1-score
- Confusion Matrix

These metrics provide a comprehensive evaluation of the model's performance and validate its effectiveness in kidney stone detection.

D. HardwareandSoftware Environment

The experiments for the KidneyAI system are conductedinaPython-basedenvironmentusingthe following configurations.

1) SoftwareConfiguration

- ProgrammingLanguage:Python3.8or higher
- CoreLibrariesandFrameworks:
  - TensorFlow 2.x / Keras – deep learning model development and Grad-CAM visualization
  - Scikit-learn – preprocessing and validation support
  - NumPy and Pandas – data handling and numerical computations
  - Matplotlib–performance visualization
- WebFramework:Flask–backend development and deployment
- DevelopmentPlatforms:
  - Jupyter Notebook and Anaconda for experimentation
  - GitandGitHub forversion control
- OperatingSystems:Windows10/11or Linux

2) Hardware Configuration

- MinimumRequirements:
  - Inteli3 processor
  - 8 GB RAM
  - 256 GB storage
- RecommendedConfiguration:
  - Inteli5/i7orAMDRyzen 5/7
  - 6 GB RAM
  - 512 GB SSD
  - NVIDIAGPU(optional)forfaster training

IV. RESULTS AND DISCUSSIONS

The experimental evaluation of the proposed KidneyAI system demonstrates its effectiveness in accuratelydetectingkidneystonesfromultrasound imagesusingdeeplearningtechniques.Theresults highlight the advantages of integrating transfer learning–based image classification with a robust validation mechanism to ensure reliable and consistent predictions.

The deep learning model successfully learned complex spatial patterns present in kidney ultrasoundimages,enablingaccurateclassification intoNormalandKidneyStoneDetectedcategories. Theuseofthe MobileNetV2 architecture with transfer learning significantly improved model performance,evenwitharelativelylimiteddataset. Themodel producedreliablepredictionsalongwith confidence scores, demonstrating strong generalizationonunseen testimages.However,like most deep learning models, raw predictions alone donotprovidesufficientinsightintohowdecisions are made, which can limit trust in medical applications.

In contrast to traditional approaches, the proposed system incorporates an image validation module thatensuresonlyrelevantkidneyultrasoundimages are processed.

This validation mechanism effectively filters out non-medical or unrelated images, preventing incorrect predictions and enhancing overall system reliability. The inclusion ofthisstepaddressesamajorlimitationobservedin many existing models, where predictions are generated regardless of input relevance.

A significant improvement in interpretability is achieved through the use of Grad-CAM visualization. Thegeneratedheatmapshighlightthe regionswithintheultrasoundimagesthatinfluence the model's predictions. Visual analysis confirms that these highlighted regions correspond to clinically relevant areas where kidney stones are likely to be present, thereby increasing confidence in the model's decision-making process. This explainabilityfeatureplaysacrucialroleinmaking the system more transparent and trustworthy for practical use.

Comparative analysis shows that the deep learning model provides accurate and consistent classification, while the validation mechanism enhances robustness by reducing false predictions. TheintegrationofbothcomponentswithinaFlask-based web application enables real-time analysis, improving usability and accessibility. The system delivers clear outputs including prediction labels, confidence scores, and image previews, making it suitable for academic and healthcare support environments.

Overall, the results demonstrate that the proposed KidneyAI framework is effective in kidney stone detection using ultrasound imaging. The combination of deep learning, validation mechanisms, and explainable AI techniques improvesaccuracy,reliability,andinterpretability.

ThesefindingsindicatethatKidneyAIisapractical and scalable solution for supporting early kidney stonedetectionand assistingmedicalprofessionals in preliminary diagnosis.

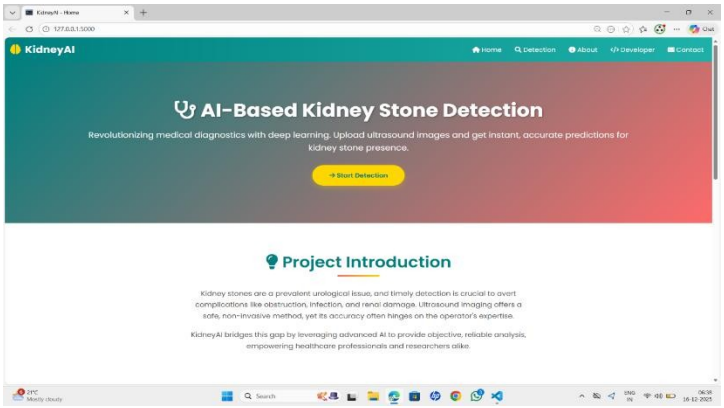


Figure2:HomePage

The home page presents an overview of the KidneyAI system designed for detecting kidney stones from ultrasound images. It highlights the purposeofusingdeeplearningforfast andreliable medical image analysis. The page provides simple navigation to begin the detection process through the main prediction module.

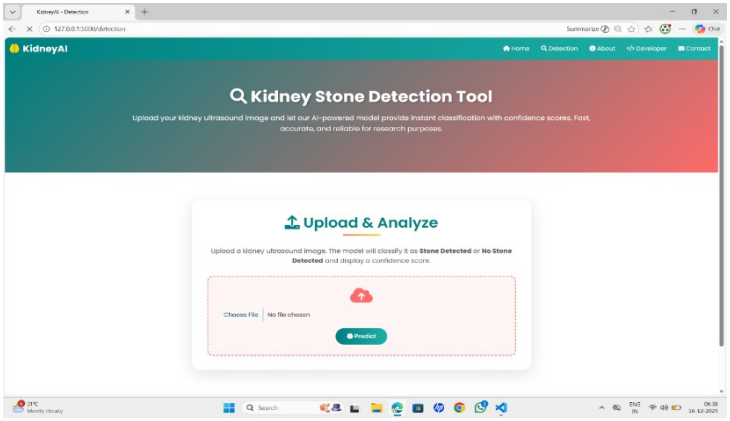


Figure3:KidneyStoneDetectionPage

Thispageallowsuserstouploadkidneyultrasound images for automated analysis using the trained deep-learning model. The system processes the uploaded image and classifies it as kidney stone detected or no stone detected with a confidence score. The interface is designed for simplicity, enabling quick and reliable prediction through a single-step upload process.

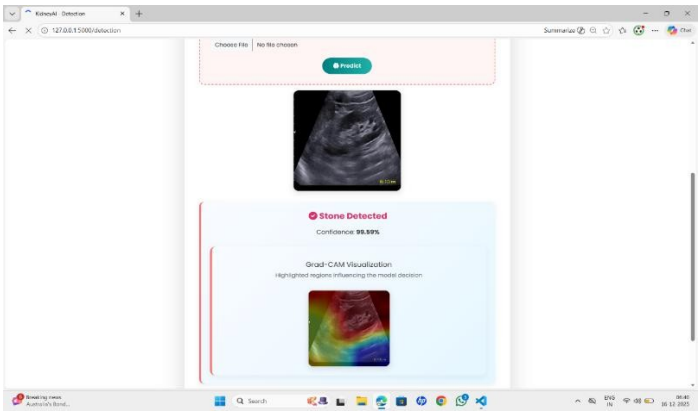


Figure4:PredictionResultPage

This page displays the prediction outcome after analyzingtheuploadedkidneyultrasoundimage.It shows whether a kidney stone is detected along with the confidence percentage generated by the deep-learningmodel.AGrad-CAMvisualizationis also provided to highlight the regions that influenced the model's decision.

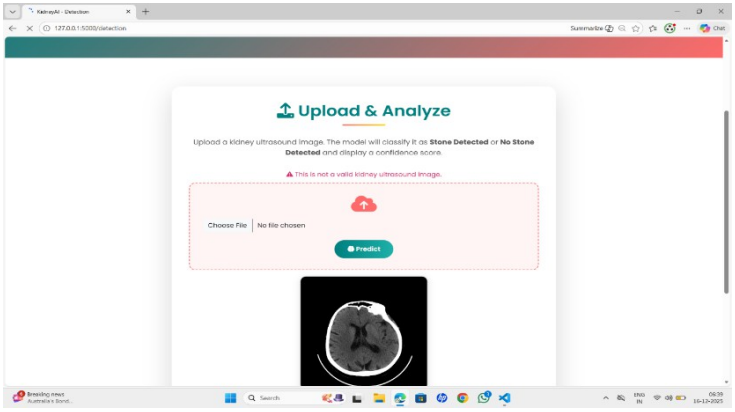


Figure5:InvalidImageHandling

This screen demonstrates the system's ability to validate uploaded images before prediction. When a non-kidney ultrasound image is provided, the application displays a clear warning message and prevents further analysis. This validation step ensures reliable predictions by allowing only relevantkidneyultrasoundimagestobe processed.

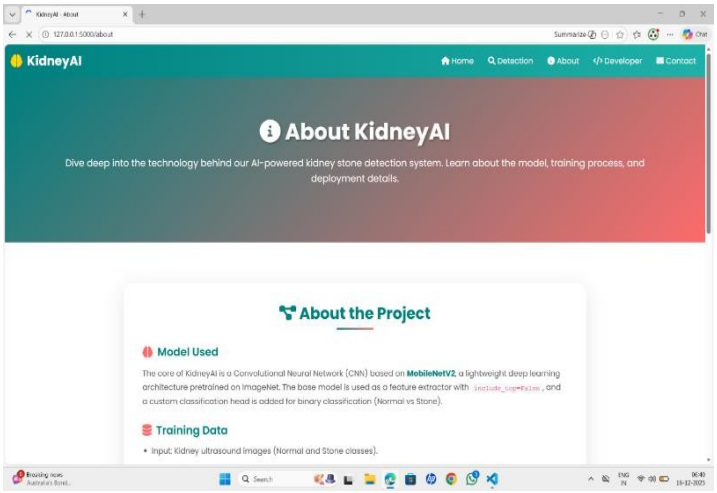


Figure6:AboutPage

This pageexplainsthetechnical backgroundofthe KidneyAI system and its underlying deep-learning approach. It describes the use of the MobileNetV2 model,trainingstrategy,anddatasetcharacteristics in a clear manner. The section helps users understand how the system performs kidney stone detection using ultrasound images.

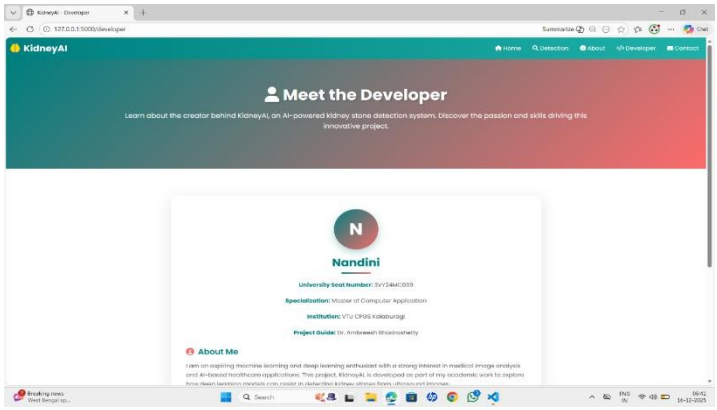


Figure7:DeveloperPage

This page presents the academic and professional detailsofthedeveloperwhodesignedtheKidneyAI system. It highlights the developer's background, institutional affiliation, and project guidance information. The section establishes project authenticity and provides context about the expertise behind the system development.

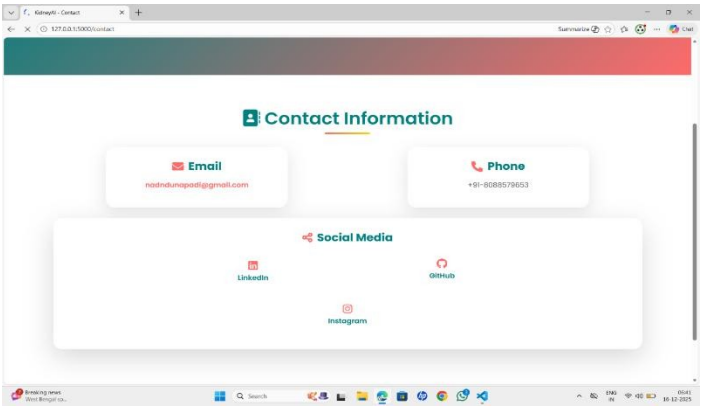


Figure8:ContactPage

This page provides official contact information for reaching the project developer. It displays email, phone number, and social media links for professional communication. The section enables users, evaluators, and researchers to connect regarding queries or project-related discussions.

This section summarizes the key characteristics of the kidney ultrasound dataset through descriptive analysis. The distribution of images highlights variationsintexture,intensity,andstructural patterns between normal kidneys and those containing stones, indicating diverse imaging conditions. The dataset also reflects differences in imagequality,noiselevels,andacquisitionsettings, which are common in real-world ultrasound data. Class-wisedistributionshowsabalancedorslightly varied representation of normal and stone-affected images, influencing model training and generalization. Feature-wise analysis reveals that specific visual patterns, such as high-intensity regions and irregular structures, play a significant roleinidentifyingkidneystones,whilesurrounding tissue characteristics contribute moderately. These observations emphasize the complexity of ultrasound image interpretation and justify the use of robust deep learning models with validation mechanisms for accurate and reliable kidney stone detection.

V. CONCLUSION & FUTURE SCOPE

The KidneyAI system successfully utilizes deep learning techniques to address the challenges of accurate and reliable kidney stone detection using ultrasound imaging.

By combining a transfer learning–based CNN model with an image validation mechanism, the proposed framework provides a robust and interpretable solution for medical image analysis. The system demonstrates that integrating deep learning with validation and explainable AI significantly enhances detection accuracy and reliability compared to conventional standalone approaches.

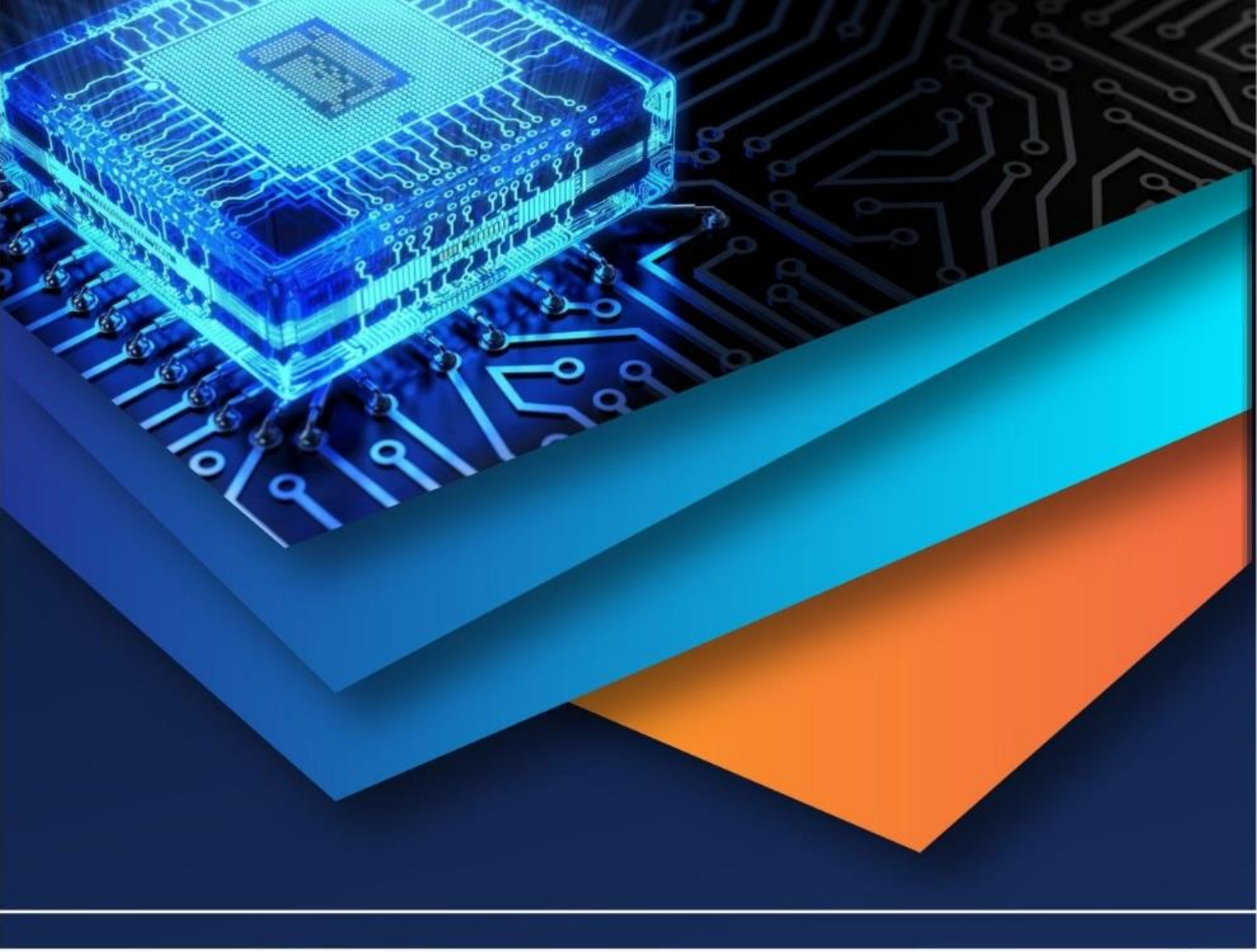
The MobileNetV2-based model effectively classifiesultrasoundimagesintonormalandkidney stone detected categories, capturing complex spatial patterns present in medical images. The inclusion of an image validation module ensures that only relevant kidney ultrasound images are processed, preventing incorrect predictions and improvingsystemrobustness.Furthermore,theuse ofGrad-CAM visualization enhances transparency byhighlightingregionsofinterestthatinfluencethe model's decision, thereby increasing trust and interpretability in the diagnostic process. Evaluationusingstandardmetricssuchasaccuracy, precision, recall, F1-score, and confusion matrix analysis confirms the effectiveness and stability of theproposedsystem.Overall,KidneyAIachieves itsobjectivebydeliveringascalable,accurate,and user-friendly platform suitable for academic research and preliminary medical screening.

Lookingahead,theKidneyAIsystemcanbefurther improved in several ways. Expanding the dataset with more diverse and high-quality ultrasound images can enhance model generalization and performance. Future work may explore advanced deep learning architectures such as EfficientNet, attention-based models, and ensemble learning techniques to further improve accuracy. The integrationofadditionalfeatures,suchasstonesize estimation, location detection, and severity analysis, can make the system more clinically useful. Incorporating advanced Explainable AI (XAI) techniques beyond Grad-CAM could provide deeper insights into model decisions. Additionally, deploying the system in real-time healthcare environments, optimizing performance using GPU acceleration, and integrating with hospital information systems can significantly enhance its practical applicability. The framework can also be extended to detect other kidney-related abnormalities, broadening its role in intelligent healthcare systems.

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