A Major Project Stage II
Report on

CNN-BASED DIAGNOSTIC SYSTEM FOR DIABETIC FOOT ULCER ANALYSIS

Submitted in partial fulfillment of the requirements for the award of the degree of

BACHELOR OF TECHNOLOGY

In

CSE (DATASCIENCE)

By

Gaddam Soujanya	**(21AG1A6722)**
Seepathi Sai Raj	**(21AG1A6759)**
Gaddam Aniketh	**(21AG1A6721)**
Vadluri Akhil	**(21AG1A6765)**

Under the guidance of
Mrs. A Sarala Devi
Associate Professor

DEPARTMENT OF CSE (DATASCIENCE)

ACE Engineering College
Ankushapur(V), Ghatkesar(M), Medchal Dist - 501301
(An Autonomous Institution, Affiliated to JNTUH, Hyderabad)
www.aceec.ac.in

A.Y: 2024-2025

DEPARTMENT OF CSE (DATA SCIENCE)

CERTIFICATE

This is to certify that the major project report entitled "***CNN-Based Diagnostic System for Diabetic Foot Ulcer Analysis***" is a Bonafide work done by ***Gaddam Soujanya (21AG1A6722), Seepathi Sai Raj (21AG1A6759), Gaddam Aniketh (21AG1A6721), Vadluri Akhil (21AG1A6765)*** in partial fulfillment for the award of Degree of BACHELOR OF TECHNOLOGY in ***CSE (Data Science)*** from JNTUH University, Hyderabad during the academic year 2024-2025. This record of bonafide work carried out by them under our guidance and supervision.

The results embodied in this report have not been submitted by the student to any other University or Institution for the award of any degree or diploma.

Mrs. A Sarala Devi	**Dr. P Chiranjeevi**	**External**
Associate Professor	Associate Professor	
Supervisor	HOD, CSE-DS	

ACKNOWLEDGEMENT

We would like to express our gratitude to all the people behind the screen who have helped us transform an idea into a real time application. We would like to express our heart-felt gratitude to our parents without whom we would not have been privileged to achieve and fulfill our dreams.

A special thanks to our General Secretary, **Prof. Y V Gopala Krishna Murthy,** for having founded such an esteemed institution. Sincere thanks to our Joint Secretary **Mrs. M Padmavathi**, for her support in doing project work. We are also grateful to our beloved principal, **Dr. K S Rao** for permitting us to carry out this project.

We profoundly thank **Dr. P Chiranjeevi**, Associate Professor and Head of the Department of Computer Science and Engineering (Data Science), who has been an excellent guide and also a great source of inspiration to our work. We extremely thank **Mr. P Ashok Kumar and Mr. Shaik Nagur Vali,** Associate Professors, Project coordinators, who helped us in all the way in fulfilling of all aspects in completion of our Major-Project.

We are very thankful to our internal guide **Mrs. A Sarala Devi** who has been an excellent and also given continuous support for the Completion of our project work.

The satisfaction and euphoria that accompany the successful completion of the task would be great, but incomplete without the mention of the people who made it possible, whose constant guidance and encouragement crown all the efforts with success. In this context, we would like to thank all the other staff members, both teaching and non-teaching, who have extended their timely help and eased our task.

Gaddam Soujanya (21AG1A6722)
Seepathi Sai Raj (21AG1A6759)
Gaddam Aniketh (21AG1A6721)
Vadluri Akhil (21AG1A6765)

DECLARATION

We here by declare that the result embodied in this project report entitled "**CNN-BASED DIAGNOSTIC SYSTEM FOR DIABETIC FOOT ULCER ANALYSIS**" is carried out by us during the year 2024-2025 for the partial fulfilment of the award of **Bachelor of Technology in Computer Science and Engineering**, from **ACE ENGINEERING COLLEGE**. We have not submitted this project report to any other Universities/Institute for the award of any degree.

G. SOUJANYA (21AG1A6722)

S. SAI RAJ (21AG1A6759)

G. ANIEKTH (21AG1A6721)

V. AKHIL (21AG1A6765)

CNN-BASED DIAGNOSTIC SYSTEM FOR DIABETIC FOOT ULCER ANALYSIS

ABSTRACT

Diabetic Foot Ulcer (DFU) is one of the most common and serious complications in diabetic patients, potentially leading to severe infections, hospitalization, and lower-limb amputations if not treated early. This project presents an intelligent, CNN-based deep learning system designed to automatically detect diabetic foot ulcers from medical foot images, aiming to assist healthcare professionals and patients in early diagnosis and prevention.

A Convolutional Neural Network (CNN) model, enhanced using transfer learning, was trained on a curated and balanced dataset containing both ulcer and non-ulcer images. To tackle the challenge of class imbalance and improve the generalization capability of the model, data resampling techniques were applied, and hyperparameter tuning was performed using Keras Tuner. The final model achieved promising results in terms of accuracy and reliability when tested on unseen data.

To make the solution accessible and user-friendly, a Flask-based web application was developed. This interface allows users to upload foot images for analysis. Upon prediction, if an ulcer is detected, the system not only notifies the user but also provides personalized dietary recommendations and medication suggestions. The diet plan includes guidelines to promote wound healing, such as consuming foods rich in fiber, vitamins, and zinc, while avoiding processed and inflammatory foods. Medication suggestions include topical and oral antibiotics, pain management options, and dressing care routines, all of which are general guidelines and should be followed under medical supervision.

By integrating AI-driven diagnosis with post-detection care guidance, this system serves as a holistic tool for managing diabetic foot ulcers. It has the potential to reduce clinical workload, increase patient awareness, and support timely intervention, especially in remote or resource-constrained areas. Overall, the project demonstrates how artificial intelligence can be effectively used in medical applications to improve patient outcomes and accessibility to healthcare support.

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1. INTRODUCTION

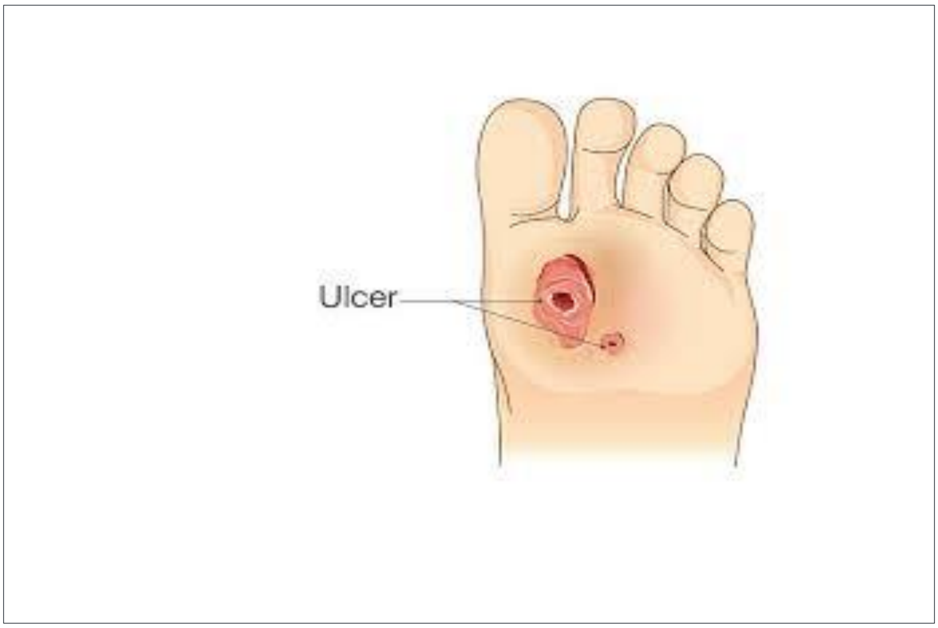
1.1 Background and Context of the Project:

Diabetes mellitus is a chronic metabolic disorder characterized by elevated blood glucose levels, which, if not managed effectively, can lead to a range of severe health complications. One such complication is the development of Diabetic Foot Ulcers (DFUs), which represent a significant burden on both the patient and healthcare systems. These ulcers occur as open sores or wounds that typically form on the bottom of the feet and are the result of prolonged high blood sugar levels that damage nerves and blood vessels. This damage often leads to peripheral neuropathy (loss of sensation in the feet) and poor circulation, increasing the likelihood of unnoticed injuries that develop into ulcers. It is estimated that 15% to 25% of diabetic patients will experience a foot ulcer at some point in their lives, and if not treated in a timely and effective manner, these ulcers can lead to serious infections, tissue necrosis, and even lower limb amputations.

Given the severity and frequency of DFUs, early detection and intervention are critical for effective treatment, reducing complications, lowering healthcare costs, and ultimately improving the quality of life of diabetic individuals. However, in many rural and resource-limited settings, consistent and early medical screening is not always feasible due to lack of trained professionals, cost barriers, or limited access to healthcare infrastructure. In such contexts, there is a pressing need for an automated, accurate, and accessible diagnostic tool that can assist healthcare workers and patients in identifying foot ulcers in their early stages.

In recent years, deep learning techniques have revolutionized the field of medical imaging and diagnostics. Among these, Convolutional Neural Networks (CNNs) have emerged as a powerful class of algorithms capable of learning spatial hierarchies of features from input images. Unlike traditional machine learning approaches that rely heavily on manual feature engineering, CNNs can autonomously learn relevant features from raw image data, making them ideal for tasks like DFU detection where visual features are critical.

This project leverages the strength of CNNs, along with transfer learning techniques, to develop a highly effective and reliable diabetic foot ulcer detection system. By utilizing pre-trained models, such as VGG16 or MobileNet, and fine-tuning them on a specific DFU dataset, the system achieves greater accuracy even with a relatively limited amount of domain-specific training data. Furthermore, to address challenges associated with class imbalance in medical datasets, the project incorporates resampling techniques such as oversampling the minority class (ulcer images) and employs hyperparameter tuning to optimize the model's performance.



Going beyond detection, this project also introduces a unique and practical addition — a Flask-based web interface that enhances user experience and accessibility. This user-friendly interface allows patients or healthcare providers to upload foot images, receive predictions, and view the diagnosis results in real time. More importantly, when an ulcer is detected, the interface offers personalized diet plans and medication recommendations to support the patient in their healing journey. These suggestions include dietary guidelines to promote tissue repair, hydration tips, foods rich in essential nutrients like Vitamin C and Zinc, and medical treatments such as topical antibiotics, dressings, and pain management strategies.

Diabetic Foot Ulcers (DFUs) are one of the most serious and common complications in individuals with diabetes, often leading to infection, hospitalization, and even amputation if not diagnosed and treated early. With the global rise in diabetes cases, timely and accurate analysis of foot ulcers have become critical for effective patient care. This project focuses on the analysis and early detection of diabetic foot ulcers using advanced data analysis and machine learning techniques. By leveraging medical imaging and clinical data, the goal is to develop a system that can assist healthcare professionals in identifying ulcer severity, predicting risks, and improving treatment outcomes. Through this research, we aim to contribute to reducing the burden of diabetic complications and enhancing the quality of life for affected patients.

In summary, this project not only addresses the technical challenges of DFU detection through CNNs and transfer learning but also prioritizes end-user empowerment and care through a comprehensive and supportive platform. It represents a significant step forward in integrating AI into holistic diabetic wound care, potentially reducing the burden of diabetic complications and improving health outcomes, especially in underserved communities.

1.2 Problem Statement and Objectives:

Diabetic Foot Ulcers (DFUs) are among the most serious and frequently occurring complications in patients living with diabetes. Globally, diabetes affects over 422 million people, and it is estimated that between 15% and 25% of them will develop foot ulcers during their lifetime. DFUs are open sores or wounds that most often appear on the bottom of the feet. If not diagnosed and treated promptly, these ulcers can progress to severe infections, tissue necrosis, and ultimately result in lower-limb amputations. Such outcomes significantly reduce the quality of life and increase mortality rates among diabetic patients, as well as place a substantial burden on healthcare systems.

Early diagnosis and continuous monitoring of diabetic foot conditions are essential to avoid complications. However, this is easier said than done, particularly in underserved and rural regions where access to qualified healthcare providers is limited. Manual foot inspections are not only labor-intensive but also susceptible to human error and subjectivity. Patients may also neglect early symptoms due to a lack of awareness, limited mobility, or diminished sensation in the feet (due to diabetic neuropathy), thereby allowing the ulcer to worsen before professional intervention can occur.

Furthermore, most patients are not equipped with knowledge about appropriate dietary practices and medications that support the healing process. This lack of awareness can delay recovery and exacerbate the condition. Thus, the challenge is twofold: providing an efficient and accurate diagnostic mechanism for early DFU detection, and equipping patients with actionable, reliable guidance for self-care, including diet and medication management.

To address these issues, the proposed project aims to develop a CNN-based intelligent system for the automatic detection of diabetic foot ulcers from medical or photographic images. Convolutional Neural Networks (CNNs) are a class of deep learning models that have demonstrated exceptional performance in visual recognition and medical imaging tasks. By training a CNN model using foot ulcer images, the system will learn to differentiate between ulcerated and non-ulcerated feet with a high degree of accuracy.

This model is further enhanced using transfer learning, which leverages the knowledge of pre-trained models to accelerate learning and improve performance on relatively small and specialized datasets. Resampling techniques are also employed to balance the dataset and ensure the model does not become biased toward one class. Additionally, hyperparameter tuning is conducted to optimize the model's learning process and achieve better generalization during testing.

Beyond the scope of image classification, this project introduces an interactive web-based interface built using Flask. This interface allows users—patients or healthcare workers—to upload foot images for instant ulcer detection. Once an ulcer is detected, the system goes a step further by offering customized dietary recommendations and medication suggestions tailored for ulcer-affected individuals. These recommendations are based on medical guidelines and focus on promoting wound healing, enhancing immunity, and preventing further complications.

The objectives of this project are as follows:

1. To design and implement a CNN-based model capable of accurately classifying images of diabetic feet into ulcerated and non-ulcerated categories.
2. To improve model performance through transfer learning, data resampling, and hyperparameter tuning techniques.
3. To build a user-friendly web application that integrates the model and allows easy upload and analysis of foot images.
4. To provide additional support in the form of dietary guidance and medication suggestions for ulcer management.
5. To promote healthcare accessibility, especially in low-resource environments where timely medical consultation is challenging.

By integrating AI with healthcare diagnostics and patient education, this project seeks to empower diabetic individuals, reduce medical dependency, and ultimately lower the risks associated with diabetic foot ulcers. The solution not only bridges a technological gap in medical imaging but also contributes to improved healthcare delivery and better patient outcomes.

1.3 The specific objectives include:

The primary objective of this project is to design and implement a robust, intelligent, and accessible system for the early detection of Diabetic Foot Ulcers (DFUs) using the capabilities of Convolutional Neural Networks (CNNs). DFUs are a leading cause of morbidity in diabetic patients, and early identification is essential to prevent further complications, including infections and amputations. In addressing this critical healthcare issue, the project outlines the following specific objectives:

1. Development of a CNN-Based Classification Model: One of the primary objectives of this project is to design and develop a Convolutional Neural Network (CNN)-based classification model capable of accurately identifying diabetic foot ulcers (DFUs) from medical or clinical foot images. CNNs are a powerful type of deep learning architecture specifically designed for image recognition tasks. They excel at automatically learning and extracting spatial hierarchies of features—such as edges, textures, and complex shapes—making them well-suited for medical image analysis where subtle variations are critical. In this project, the CNN model will be trained on a labeled dataset consisting of ulcerated and non-ulcerated foot images. Through multiple convolutional and pooling layers, the model will learn to detect key indicators of ulcers such as discoloration, tissue degradation, and abnormal skin patterns. The model's performance will be evaluated using metrics such as accuracy, precision, recall, F1-score, and AUC-ROC. Ultimately, the goal is to build a reliable and efficient CNN-based tool that can assist healthcare professionals in the early detection and classification of DFUs, even in resource-limited settings.

2. Utilization of Transfer Learning for Model Efficiency: Since high-quality labeled medical datasets are often limited, the project employs transfer learning to leverage the power of pre-trained models like VGG16, ResNet, or MobileNet. These models, trained on massive image datasets such as ImageNet, already have learned feature representations that can be adapted to medical imaging tasks. This approach accelerates training, improves model generalization, and ensures high performance even on smaller, domain-specific datasets.

3. Application of Data Preprocessing and Resampling Techniques: To ensure the model is trained on a balanced and clean dataset, the project involves comprehensive preprocessing steps. These include resizing images to a uniform shape, normalizing pixel values, and augmenting the dataset using techniques such as rotation, flipping, and zooming. Additionally, class imbalance—often a problem in medical datasets—is addressed using resampling techniques such as oversampling the minority class or applying Synthetic Minority Over-sampling Technique (SMOTE). These strategies aim to reduce model bias and improve the classification accuracy for both classes.

4. Hyperparameter Tuning and Optimization: To maximize the performance of the CNN model, systematic tuning of hyperparameters such as learning rate, batch size, optimizer selection, number of layers, and activation functions is performed. Grid search, random search, or Bayesian optimization methods may be used to identify the optimal parameter settings. This step is crucial to ensure that the model achieves high sensitivity and specificity in detecting DFUs. Additionally, early stopping techniques are employed to monitor the validation loss and halt training when overfitting begins, thereby preserving the model's generalization ability. Validation curves and learning curves are also analyzed to understand the model's behavior over training epochs, helping refine both the model architecture and training strategy.

5. Integration into a Web-Based User Interface: Another major objective is to embed the trained model into a user-friendly, responsive web application using frameworks such as Flask or Django. This interface allows patients, caregivers, and healthcare professionals to upload foot images and receive real-time diagnostic feedback. The interface is designed to be intuitive and accessible even to users with minimal technical background, ensuring wide usability and adoption. To maintain user trust and comply with healthcare regulations, the application will implement strong data security and privacy measures, including encrypted image uploads and secure storage protocols. Additionally, the system will be designed with future integration in mind, allowing seamless connectivity with Electronic Health Records (EHRs) to enable continuous monitoring, clinical documentation, and enhanced patient care.

6. Providing Personalized Diet Plans and Medication Suggestions: The system goes beyond mere detection by offering holistic support to patients. Based on the detection outcome, users identified with DFUs will receive personalized diet recommendations rich in nutrients that promote wound healing and immune response. Additionally, medication suggestions and general care tips are provided, guided by medical guidelines and expert consultation. This helps bridge the gap between detection and treatment, promoting better self-care and informed health decisions.

7. Enhancing Healthcare Accessibility and Supporting Rural Outreach: By offering a digital platform that can function on commonly available devices (like smartphones or computers), this system aims to make advanced medical diagnostics available to underserved and rural communities where healthcare infrastructure is limited. This democratization of technology ensures that timely ulcer detection and care guidance are no longer limited to urban healthcare centers. It also significantly reduces the need for frequent and costly travel to distant hospitals, easing the financial and physical burden on patients. Moreover, the platform empowers frontline health workers and community health volunteers by providing them with a reliable diagnostic tool, enabling early intervention and better patient outcomes even in low-resource settings.

8. Evaluation and Performance Validation: The final objective is to thoroughly evaluate the system using various performance metrics such as accuracy, precision, recall, F1-score, and ROC-AUC. Confusion matrices will be used to assess classification quality, and cross-validation techniques will ensure robustness across different data splits. Additionally, model performance will be compared with baseline classifiers to highlight improvements achieved through the proposed approach. Evaluation will also include testing on unseen real-world data to validate the system's generalizability and effectiveness in practical scenarios. Furthermore, feedback from medical experts will be incorporated to assess the clinical relevance and usability of the model's predictions, ensuring the solution aligns with real-world diagnostic needs.

In conclusion, the project stands as a comprehensive initiative that seamlessly integrates AI-driven diagnostics with personalized healthcare support, marking a transformative shift in diabetic foot care management. By leveraging the power of Convolutional Neural Networks, the system not only enables early and accurate detection of diabetic foot ulcers but also bridges the gap between clinical expertise and patient accessibility. Its user-friendly interface and real-time diagnostic feedback empower individuals to take charge of their health, fostering a culture of awareness and proactive care. This approach is especially beneficial for patients in rural or under-resourced regions where access to medical specialists is limited, making the system a vital tool in democratizing healthcare.

Beyond diagnosis, the system's value lies in its holistic design — offering dietary advice, medication recommendations, and wound care guidance tailored to the user's condition. This patient-centric model transforms a passive diagnostic tool into an interactive healthcare assistant, promoting education and continuous engagement. It encourages diabetic patients to adopt healthier lifestyles while ensuring they receive timely support for managing complications. As the system evolves, its scalability and adaptability open doors to future innovations, such as multilingual support, integration with wearable sensors, and mobile deployments, ultimately contributing to improved quality of life and reduced healthcare burdens worldwide.

1.4 Significance and Motivation:

Diabetes is a global health concern affecting millions of people, with its prevalence increasing at an alarming rate. One of the most severe and costly complications of diabetes is Diabetic Foot Ulcer (DFU), which affects up to 25% of diabetic individuals at some point in their lives. DFUs are open sores or wounds, usually located on the sole of the foot, that, if left untreated, can lead to serious infections, gangrene, and ultimately lower-limb amputations. These complications are not only life-threatening but also lead to substantial physical, emotional, and financial burdens on patients and healthcare systems alike.

The significance of this project lies in its proactive approach to addressing this critical issue through the application of advanced technologies—namely, deep learning and computer vision. While early detection and treatment can dramatically reduce the risk of amputation and improve patient outcomes, access to skilled healthcare professionals is not uniformly available, particularly in rural or economically disadvantaged regions. In such areas, patients often lack routine screening and clinical expertise, resulting in late-stage diagnoses and poor prognoses. This project seeks to fill that gap by developing an automated, intelligent diagnostic tool that uses Convolutional Neural Networks

(CNNs) to analyze images of the foot and detect the presence of ulcers with high accuracy.

Diabetic Foot Ulcers (DFUs) are a major health concern affecting millions of diabetic patients worldwide. They account for a significant number of diabetes-related hospital admissions and are one of the leading causes of lower limb amputations. Early diagnosis and timely intervention are crucial to prevent severe complications, yet many cases go undetected or are diagnosed too late due to a lack of proper screening and monitoring tools.

The motivation behind this project stems from the urgent need for accurate, automated, and accessible methods to analyze and detect diabetic foot ulcers. Traditional manual diagnosis can be time-consuming, subjective, and dependent on clinical expertise. By integrating machine learning and image analysis techniques, this project aims to assist healthcare professionals in identifying DFUs more efficiently and consistently.

The motivation for this project stems from several key observations. Firstly, traditional diagnostic approaches for DFUs are heavily reliant on manual inspection by trained clinicians. These methods are not only time-consuming and subjective but also inconsistent, as the accuracy of diagnosis can vary significantly between practitioners.

In contrast, deep learning models—particularly CNNs—have shown exceptional performance in various image classification tasks, including medical imaging. CNNs can learn and extract complex patterns from foot images, enabling early and accurate detection of ulcers without manual intervention. This ensures consistency, efficiency, and scalability, especially when deployed in areas with limited medical infrastructure.

Another major motivating factor is the increasing affordability and accessibility of AI technology. With the advent of open-source machine learning frameworks and pre-trained models, it has become feasible to build powerful diagnostic systems at a fraction of the cost of traditional medical equipment. This project utilizes transfer learning to fine-tune pre-trained CNN models, reducing the computational resources and data required while still achieving high accuracy. Such a system, when integrated into a web-based interface, can be easily accessed by healthcare professionals or patients with internet access and a mobile device or computer.

Beyond detection, the project also seeks to enhance patient education and self-care by providing additional resources such as personalized diet plans and medication suggestions. Many patients with DFUs are unaware of the importance of proper nutrition, wound care, and timely medication. By incorporating these features, the project aims to empower patients to actively manage their condition, thereby reducing dependency on in-person consultations and promoting better overall health management.

A key driver of motivation for this project is the inefficiency and inconsistency of manual diagnosis. Visual inspection by healthcare workers, although effective in expert hands, is subject to human error, fatigue, and variability in experience. Additionally, clinical settings are often overwhelmed, reducing the time available for thorough examinations. CNNs, by contrast, can process thousands of images with consistent accuracy, identify subtle patterns that may be missed by the human eye, and work tirelessly 24/7. The use of transfer learning further enhances model performance by building on pre-trained networks, making the solution practical even with limited medical datasets.

From a broader perspective, the project embodies the intersection of artificial intelligence and healthcare, highlighting how AI can be used not just for automation but also for impactful social good. It demonstrates how technology can be leveraged to solve real-world health challenges, especially in underserved communities. By offering a low-cost, reliable, and user-friendly diagnostic tool, this system can significantly improve the quality of life for diabetic patients, reduce the incidence of amputations, and alleviate the strain on healthcare systems.

In conclusion, the significance and motivation behind this project are deeply rooted in the desire to democratize healthcare access, enhance early diagnosis, and support better patient outcomes using AI. This project is not only a technological innovation but also a compassionate step toward more inclusive, efficient, and intelligent healthcare delivery.

2. LITERATURE SURVEY

The use of artificial intelligence (AI), particularly deep learning, in medical imaging has gained substantial traction in recent years. In the context of diabetic foot ulcers (DFUs), early detection and treatment are critical to preventing severe outcomes such as infection, hospitalization, or amputation. Numerous studies have explored the use of Convolutional Neural Networks (CNNs) for automated DFU classification, as CNNs excel in feature extraction and image recognition tasks.

Goyal et al. (2018) introduced a CNN model that could classify diabetic foot ulcer images using a pre-trained AlexNet architecture, achieving significant accuracy through transfer learning. Similarly, Alzubaidi et al. (2020) proposed an improved deep CNN model, DFU_QUTNet, which was trained on the public Diabetic Foot Ulcer Challenge (DFUC) dataset. Their model achieved over 90% classification accuracy and highlighted the potential of CNNs in clinical applications.

Another important work by Wang et al. (2021) employed VGGNet and ResNet models for feature extraction in DFU detection. They found that deeper architectures performed better in capturing the intricate textures and colors of ulcerated skin. Preprocessing steps like resizing, normalization, and data augmentation improved the robustness of these models.

Recent studies also emphasize the role of transfer learning in enhancing performance when dataset size is limited. By fine-tuning models pre-trained on large datasets like ImageNet, researchers could leverage learned features for specific tasks like ulcer detection. Transfer learning has shown promising results in DFU detection by reducing training time and increasing accuracy even with smaller medical datasets.

In addition to image classification, researchers have integrated patient support systems. A study by Kirthika and Rajalakshmi (2022) proposed a mobile health application that not only classifies ulcer severity but also provides care instructions and alerts. This aligns with the current project's approach, which includes diet and medication suggestions post-prediction, aiming to enhance patient outcomes and engagement.

Furthermore, datasets play a crucial role in model performance. Many research efforts utilize the DFUC dataset or create custom datasets in collaboration with healthcare institutions. However, dataset imbalance—where non-ulcer images outnumber ulcer ones—is a common challenge. Techniques like resampling and synthetic image generation (via GANs or SMOTE) are employed to mitigate this issue.

Despite advances, many models still face challenges such as overfitting, misclassification due to lighting variations or skin tone diversity, and generalizability across populations. Researchers are also exploring hybrid models that combine CNNs with attention mechanisms or ensemble learning to enhance prediction stability and interpretability.

In summary, the literature demonstrates a strong foundation for using CNNs in diabetic foot ulcer detection. Models like ResNet, VGGNet, and Inception have shown reliable performance when used with proper preprocessing, transfer learning, and data balancing techniques. However, there is still room for improvement, particularly in building explainable AI systems that can aid clinicians and empower patients. This project builds upon existing research by integrating an intuitive web interface with not only detection capability but also personalized care recommendations, thereby offering a more holistic approach to managing diabetic foot complications.

2.1 Existing System:

Currently, the detection and diagnosis of Diabetic Foot Ulcers (DFUs) primarily rely on manual inspection by healthcare professionals. Clinicians assess the affected area based on visual symptoms such as skin discoloration, ulcer depth, and signs of infection. This method, though effective in many cases, is highly subjective and varies with the experience and expertise of the medical practitioner. Moreover, in rural or underdeveloped regions, access to trained professionals and timely diagnosis is limited, increasing the risk of complications such as infections, gangrene, and ultimately amputations.

Some existing automated systems have been developed using traditional machine learning techniques. These systems often require hand-crafted features and domain-specific image preprocessing techniques, such as edge detection, texture analysis, and color segmentation. However, these methods have limitations in capturing complex visual patterns and textures of ulcers, and they often underperform when faced with diverse real-world images.

Recently, deep learning-based approaches, particularly using Convolutional Neural Networks (CNNs), have been explored in research settings. Models like AlexNet, VGGNet, and ResNet have shown promise in DFU image classification tasks. These systems utilize transfer learning and fine-tuning techniques to adapt pre-trained models on medical image datasets. While these approaches have improved accuracy and consistency, they are mostly limited to academic and experimental environments and often lack user-friendly interfaces for patient or clinician use.

Additionally, most of these systems focus solely on classification and lack integration with patient care workflows. They do not provide post-diagnosis support such as personalized diet plans or medication recommendations, which are essential for holistic treatment. Thus, while there are strides in automation using AI, there is still a gap in accessible, reliable, and user-centric system for DFU detection and patient guidance.

2.1.1 Limitations of Existing System:

1. Manual Diagnosis and Human Error

Most current systems rely heavily on manual examination by healthcare professionals. These assessments are subjective, time-consuming, and prone to human error, leading to misdiagnosis or delayed detection of ulcers.

2. Limited Availability of Skilled Professionals

In rural or under-resourced areas, there is a significant shortage of trained podiatrists or medical personnel equipped to perform regular foot screenings. This leads to late detection and poor management of diabetic foot complications.

3. Lack of Automation

Traditional systems do not leverage artificial intelligence or deep learning for automated detection, limiting scalability and quick decision-making, especially in emergency or remote scenarios.

4. Absence of Integrated Support

Most existing systems only focus on detecting the ulcer without providing further guidance. They do not offer personalized diet plans, wound care instructions, or medication suggestions, which are essential for holistic care.

5. Data Imbalance and Poor Model Generalization

Some AI-based systems struggle due to imbalanced datasets (more non-ulcer images than ulcer ones), leading to biased predictions and poor generalization on real-world data.

6. Poor User Experience

Many existing tools are not user-friendly or accessible via web or mobile platforms. Patients and caregivers may find it difficult to interact with these systems without medical or technical knowledge.

7. Language and Literacy Barriers

Patients from different regions may struggle to understand system outputs or instructions if the platform does not support multiple languages or assumes a certain literacy level.

8. Limited Clinical Validation

Many AI models are trained and tested in research environments but lack thorough clinical validation, which limits their acceptance and integration into real-world healthcare systems.

9. High Computational Requirements

Deep learning models, especially those involving high-resolution medical images, require significant computational resources and may not be feasible to deploy on low-power devices in rural clinics.

10. Privacy and Data Security Concerns

Medical data is highly sensitive. Collecting, storing, and using patient data for analysis raises ethical concerns and demands strict compliance with data privacy regulations like HIPAA or GDPR.

2.2 Proposed System:

The proposed system aims to enhance diabetic foot ulcer (DFU) detection through the use of Convolutional Neural Networks (CNNs). The approach begins with preprocessing the input images, including resizing and normalizing them to ensure compatibility with the CNN model. The system takes advantage of transfer learning, where a pre-trained model (such as ResNet or EfficientNet) is fine-tuned to detect DFUs. Transfer learning is particularly beneficial in this case, as it allows the model to achieve high accuracy even with a relatively small dataset of DFU images. This method enables the model to learn crucial features that distinguish between ulcer and non-ulcer conditions, improving both the speed and accuracy of diagnosis. The model's output is binary, classifying images into either "Ulcer Detected" or "No Ulcer Detected."

Once preprocessing is complete, the images are passed into a fine-tuned CNN model. This model utilizes transfer learning, where a pre-trained network (initially trained on large datasets like ImageNet) is adapted for DFU classification. Transfer learning significantly boosts model accuracy and reduces the need for extensive medical image datasets, which are often limited. The system performs binary classification, categorizing each image as either "Ulcer Detected" or "No Ulcer Detected," with high confidence. This clear output supports rapid decision-making and is easy to interpret by users without clinical expertise.

After detecting the presence of a diabetic foot ulcer, the system goes a step further by providing personalized recommendations to the user. These suggestions include dietary advice such as the consumption of fiber-rich foods, Vitamin C, and Zinc to promote healing. Additionally, the system recommends medications like topical antibiotics, pain relievers, and proper wound care practices, such as regular dressing of the ulcer. The goal is to not only detect DFUs but also support the patient's recovery process with actionable, medically sound recommendations.

Beyond detection, the system distinguishes itself by offering personalized recommendations tailored to the patient’s condition. If an ulcer is detected, the user receives dietary guidance that includes suggestions for consuming fiber-rich foods, Vitamin C, Zinc, and other essential nutrients to promote healing. In parallel, the system recommends medications such as topical antibiotics, pain relievers, and wound care instructions like regular cleaning and dressing. These actionable insights transform the system from a diagnostic tool into a supportive healthcare assistant, enabling proactive self-care and improved health literacy.

A key strength of the proposed system lies in its robust image preprocessing and augmentation pipeline, which ensures that the CNN model can generalize well despite the inherent variability in diabetic foot images. Factors such as lighting conditions, foot orientation, and image resolution can vary widely, especially when images are captured outside clinical environments. By incorporating techniques like rotation, zoom, shear, and flipping during training, the system becomes more resilient to such inconsistencies, improving the model's ability to accurately detect ulcers in diverse real-world conditions. This preprocessing also normalizes the data, ensuring consistent input quality and facilitating faster and more stable model training.

Clinically, the system has the potential to revolutionize early detection and management of diabetic foot ulcers by bridging the gap between patients and healthcare providers. Early identification of ulcers dramatically reduces the risk of severe complications such as infections or amputations. This tool enables patients to monitor their foot health regularly from home, empowering them with timely information and reducing the burden on healthcare systems. For medical professionals, the diagnostic assistance can serve as a second opinion, especially in remote or underserved areas where specialists are scarce. Additionally, the personalized treatment suggestions can improve adherence to care protocols, leading to better patient outcomes.

Despite its promise, several challenges must be addressed to ensure effective deployment and adoption of the system. One significant issue is the quality and diversity of training data; DFU images should encompass different skin tones, ulcer stages, and comorbid conditions to avoid bias and improve generalization. Furthermore, integrating the system into existing healthcare workflows requires interoperability with electronic health records and compliance with privacy regulations such as HIPAA or GDPR. User trust is also critical — the system should clearly communicate its diagnostic confidence and limitations, encouraging users to seek professional medical advice, when necessary, rather than relying solely on AI outputs.

Looking forward, the system’s development can be extended by incorporating multi-modal data inputs, such as thermal imaging, patient medical history, and sensor-based monitoring of foot pressure or temperature changes. This multi-faceted approach could enhance early warning capabilities and provide a more comprehensive assessment of ulcer risk and healing progress. Moreover, leveraging advances in explainable AI will help make model decisions transparent, fostering greater confidence among users and healthcare providers. The integration of AI chatbots or virtual assistants could further personalize user interactions, offering guidance, reminders, and support throughout the treatment journey. Ultimately, continuous collaboration between AI researchers, clinicians, and patients will be essential to evolve this platform into a trusted and indispensable component of diabetic care.

The user interface of the system is designed to be simple and intuitive, enabling both patients and healthcare providers to upload images and receive diagnostic results instantly. This accessibility is critical, especially in areas with limited access to healthcare facilities. The system's ability to offer personalized treatment plans and recommendations makes it an invaluable tool for early intervention and ongoing care. Moreover, the system can be integrated into mobile or web-based platforms, further increasing its reach and usability. By continuously learning from new data, the system also improves over time, offering more accurate diagnoses and better recommendations.

The system architecture is designed to be lightweight so that it can even be deployed on mobile devices. Future iterations may include AI-powered chatbot assistance within the web interface, which can guide users through the care process in natural language, increasing accessibility and engagement.

In conclusion, the proposed CNN-based DFU detection system is an innovative step toward intelligent, accessible, and holistic diabetic care. By combining high-accuracy image classification with personalized healthcare advice, it addresses both the diagnostic and educational needs of patients. Its scalability, user-friendliness, and adaptability make it a promising tool for large-scale adoption, particularly in regions with limited access to specialist healthcare services.

3. REQUIREMENT ANALYSIS

3.1 Software Requirements:

1. Programming Language:

- **Python**: A widely used language for machine learning and NLP due to its rich ecosystem of libraries and frameworks.

2. Machine Learning Frameworks:

- **TensorFlow/Keras**: TensorFlow and its high-level API Keras will be used to build, train, and evaluate the Convolutional Neural Network (CNN) model for DFU detection. These frameworks provide efficient tools for model construction, training, and fine-tuning (transfer learning).
- **OpenCV:** OpenCV will be used for image preprocessing tasks, such as resizing, normalizing, and enhancing input images.

3. Libraries:

- **NumPy**: Essential for handling numerical operations, particularly for image data processing and manipulation.
- **Pandas**: Used for managing datasets, particularly if you're working with CSV files or any tabular data.
- **Matplotlib/Seaborn**: For visualizing model performance (e.g., loss/accuracy curves, confusion matrices) and for plotting results.
- **scikit-learn**: Useful for performing tasks such as data splitting, evaluation metrics, and hyperparameter tuning.

4. Operating System (OS):

- **Windows 10**: It provides the environment for development, testing, and execution of the CNN based diagnostic system for diabetic foot ulcer analysis.

5. Integrated Development Environment (IDE):

- **Visual Studio Code or Jupyter Notebook**: This IDE provides an interactive and efficient platform for writing, debugging, and testing code.

6. Web Framework:

- **Flask**: Flask will be used for developing the web-based user interface. It's a lightweight framework that allows for quick deployment and easy integration with machine learning models.
- **HTML/CSS/JavaScript**: For designing the frontend, ensuring a user-friendly interface where users can upload images and receive diagnostic results.

3.2 Hardware Requirements:

1. Processor:

Dual-core processor, such as Intel Core i3 or equivalent. This should provide sufficient processing power for data processing and model training, especially for machine learning tasks.

2. RAM:

4GB of RAM. This amount of memory should be adequate for running the Python scripts, Jupyter Notebook, and other software components simultaneously without significant performance issues.

3. Storage:

50GB of available disk space. This storage capacity should accommodate the installation of necessary software packages, datasets, and any additional files generated during the project.

4. Internet Connectivity:

Internet connectivity is required for data collection, downloading software packages, and accessing online resources for model updates, if applicable.

3.3 Functional Requirements:

Here are the functional requirements for the CNN Based Diagnostic System for Diabetic Foot Ulcer Analysis:

1. **Image Upload and Processing:**

The system should allow users to upload images of their feet for analysis. It should accept common image file formats like JPEG, PNG, and BMP.

2. **Ulcer Detection:**

The system should analyze the uploaded image and detect whether a diabetic foot ulcer is present or not.

3. **Diet Plan Recommendations:**

Based on the detection result, the system should suggest a personalized diet plan for ulcer-affected patients.

4. Medication Suggestions:

The system should provide a list of medications or treatments for ulcer management, based on the detected condition.

3.4 Non-Functional Requirements:

Here are the non-functional requirements for for the CNN Based Diagnostic System for Diabetic Foot Ulcer Analysis:

1. **Performance:**

   The system should respond quickly to user requests, especially image uploads and predictions.

2. **Scalability:**

   The system should be able to handle an increasing number of users or requests over time without significant degradation in performance.

3. **Reliability:**

   The system should be highly reliable and consistently available to users.

4. **Usability:**

   The system should provide an intuitive and easy-to-navigate interface.

5. **Security:**

   The system should ensure that sensitive user data, including uploaded images and personal details, is protected.

6. **Availability:**

   The system should be available to users 24/7, with minimal downtime.

7. **Maintainability:**

   The system should be easy to maintain and update with minimal effort.

4. SYSTEM ANALYSIS

4.1 Methodology:

The methodology for the CNN-Based Diagnostic System for Diabetic Foot Ulcer Analysis is structured around several key steps, combining machine learning with deep learning techniques to create an effective diagnostic tool. The process includes data collection, preprocessing, model training, evaluation, deployment, and user interface development. To improve the performance and generalization of the model, data augmentation techniques such as rotation, flipping, scaling, and brightness adjustment are applied to increase the diversity of the dataset. Convolutional Neural Networks (CNNs) are then used to automatically extract important features from the ulcer images, enabling the system to accurately distinguish between different ulcer types and severity levels. Additionally, the model is continuously optimized after deployment by retraining with new data, allowing it to adapt to a wider range of patient conditions and improve diagnostic accuracy over time.

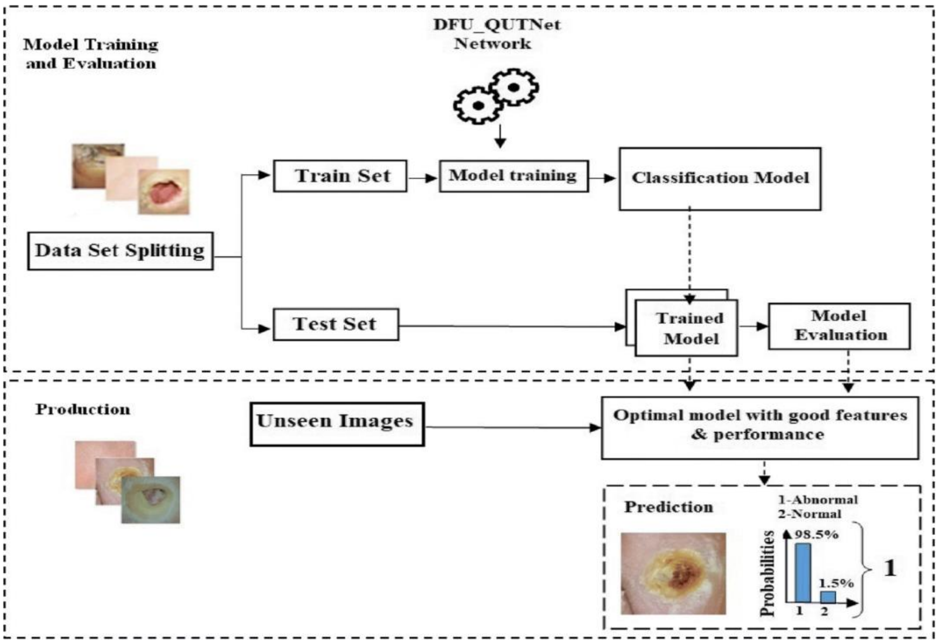


Fig: Methodology

1. Data Collection:

The first step involves gathering a comprehensive dataset containing images of both diabetic foot ulcers and non-ulcer feet. These images are sourced from publicly available medical datasets or from collaborations with medical institutions, ensuring a balanced distribution between ulcer and non-ulcer cases. The dataset consists of high-quality, labeled images. To enhance the model's learning capabilities, metadata such as patient age, medical history, and ulcer location may also be collected alongside the images. Furthermore, ethical considerations, including patient consent and data anonymization, are strictly followed to ensure compliance with medical data privacy regulations.

2. Data Preprocessing:

- **Image Resizing**: Images are resized to a standard size, typically 224x224 pixels, to match the input requirements of the Convolutional Neural Network (CNN).
- **Normalization**: Pixel values are normalized to a range of [0, 1] by dividing each pixel by 255, which helps improve model convergence.
- **Augmentation**: Data augmentation techniques such as rotation, zooming, flipping, and brightness adjustments are applied to artificially expand the dataset, improving the model's robustness to various input conditions.

3. Model Development:

- A Convolutional Neural Network (CNN) is developed to classify foot images as ulcer or non-ulcer. The CNN model is chosen because it excels at image classification tasks by learning features such as edges, textures, and patterns directly from the images.

- **Transfer Learning**: Pretrained models such as VGG16, ResNet, or InceptionV3 are fine-tuned on the DFU dataset. Transfer learning allows the model to leverage knowledge from models trained on large-scale datasets, which significantly reduces training time and improves accuracy.
- **Model Architecture**: The model consists of several convolutional layers, pooling layers, and fully connected layers to extract features and make predictions. The final layer uses a sigmoid activation function for binary classification (ulcer vs non-ulcer).

4. Hyperparameter Tuning:

Hyperparameters such as learning rate, batch size, number of epochs, and dropout rate are optimized using techniques like grid search or random search. This step is critical to achieve the best performance for the model. In addition to traditional methods, more advanced optimization techniques like Bayesian optimization or Hyperband may be used to efficiently explore the hyperparameter space. Cross-validation is also employed during tuning to ensure that the selected parameters generalize well to unseen data. Proper tuning helps prevent overfitting, accelerates convergence during training, and significantly improves the overall diagnostic accuracy of the system.

5. Model Evaluation:

- After training, the model is evaluated using metrics like accuracy, precision, recall, F1-score, and ROC-AUC. These metrics ensure that the model is not only accurate but also performs well in identifying both ulcer and non-ulcer cases.
- Cross-validation techniques such as k-fold cross-validation may be used to assess the generalizability of the model.
- A confusion matrix is analyzed to understand the distribution of

true positives, true negatives, false positives, and false negatives, helping identify any specific areas where the model may be underperforming.

- Class-wise performance metrics are also reviewed, especially in cases of class imbalance, to ensure that minority classes (e.g., rare ulcer types) are correctly identified.
- The evaluation process may include external validation using an independent dataset to further verify the model's robustness in real-world clinical scenarios.

6. Deployment:

- The trained model is saved in a file format compatible with deployment (e.g., .h5 for Keras models). It is then integrated into a Flask-based web application that allows users to upload images and receive real-time predictions.
- **Web Application**: A simple user interface is developed using HTML, CSS, and JavaScript, allowing users to upload foot images for ulcer detection. The model predicts whether the image contains an ulcer or not and provides additional suggestions such as diet plans and medication for ulcer patients.

7. Diet Plan and Medication Recommendations:

When an ulcer is detected, the system suggests a personalized diet plan and medication options. The diet plan focuses on foods that promote healing, such as high-fiber and vitamin-rich foods, while the medication section includes suggestions for topical and oral treatments, along with general care guidelines for diabetic foot ulcers.

- Recommendations are tailored based on patient-specific factors such as blood sugar levels, age, weight, and comorbidities to ensure safe and effective care.

- The system may integrate with electronic health records (EHRs) to align its suggestions with existing prescriptions and medical history, avoiding potential drug interactions.
- Alerts or reminders can be generated for patients to follow their diet, take medications on time, and schedule follow-up consultations, thus supporting better adherence to treatment plans.

4.2 Modules

4.2.1. Data Acquisition Module

This module is responsible for collecting and organizing the dataset of foot images. The dataset consists of two main categories: ulcer and non-ulcer images. These images can be collected from publicly available datasets, medical research sources, or hospital records (with proper anonymization and permissions). The collected images are labeled accordingly, forming the ground truth for training and testing the model.

- The module may also support the inclusion of associated metadata such as patient age, gender, ulcer location, and severity level, which can be used for further analysis and personalization.
- Quality control mechanisms are implemented to filter out low-resolution, unclear, or duplicate images to maintain a high-quality dataset.
- The module can be designed for future scalability, allowing new images to be added periodically for model retraining and continuous improvement.

4.2.2. Data Preprocessing Module

Before feeding the images into the neural network, preprocessing is essential to ensure that the data is clean, consistent, and suitable for deep learning models. This module handles the following key steps:

- **Resizing**: All input images are resized to a uniform dimension (e.g., 224x224 pixels for MobileNet) to match the input requirements of the chosen CNN architecture. This ensures that the network receives standardized input shapes, which is crucial for efficient model training and inference.
- **Normalization:** Pixel values are normalized, typically scaling them from a range of 0–255 to 0–1. This brings consistency across the dataset, helps in faster convergence during training, and prevents issues related to differing pixel intensity scales.
- **Data Augmentation**: To enhance the diversity of the dataset and prevent overfitting, data augmentation techniques are applied. These include rotation, zooming, horizontal and vertical flipping, shifting, and brightness adjustments. This step creates variations of the existing images, simulating different real-world conditions without needing additional manual data collection.
- **Splitting the Dataset:** The preprocessed dataset is divided into training, validation, and test sets, typically in ratios like 70:15:15 or 80:10:10. This separation ensures that the model is evaluated on unseen data, enabling a more accurate assessment of its generalization capabilities.
- **Noise Removal and Enhancement (optional):** In some cases, additional preprocessing steps like noise filtering (e.g., Gaussian blur) or contrast enhancement may be applied to improve image clarity, especially if the dataset includes images from different lighting or imaging conditions.

4.2.3. Model Training Module (CNN / Transfer Learning)

This module is responsible for training the core deep learning model that will perform the classification of foot images as either ulcer or non-ulcer. It uses either a custom-built Convolutional Neural Network (CNN) or a pre-trained model through transfer learning, such as MobileNet, VGG16, or ResNet, depending on the trade-off between performance and computational resources.

- **Transfer Learning:** Transfer learning is employed by leveraging the feature extraction capabilities of models pre-trained on large datasets like ImageNet. Only the top layers of the network are retrained on the ulcer dataset, significantly reducing training time and improving performance even with limited data. Implementing binary classification (ulcer vs non-ulcer).
- **Binary Classification:** The training architecture is designed for binary classification (ulcer vs non-ulcer). The final dense layer typically uses a sigmoid activation function to output probabilities, and binary cross-entropy is used as the loss function to optimize classification performance.
- **Model Saving:** Once the model is trained and validated, it is saved in formats such as .h5 (for Keras models), enabling its reuse during prediction or deployment. This persistent storage makes it possible to load and run the model without retraining.
- **Training Monitoring:** During training, metrics like accuracy and loss are tracked across epochs using tools such as TensorBoard or matplotlib visualizations. Early stopping and learning rate schedulers may be used to prevent overfitting and optimize training efficiency.
- **Hardware Utilization:** To accelerate training, especially for deep models, GPU support is used via platforms like TensorFlow-GPU or PyTorch with CUDA. This reduces model training time significantly compared to CPU-based training.
- **Custom Callbacks:** The module may include callbacks for automatic model checkpointing, early stopping, and dynamic learning rate adjustments, allowing for more controlled and efficient training sessions.

4.2.4. Prediction Module

The Prediction Module utilizes the trained and saved model to perform inference on new, unseen image data provided by users. This is a crucial component of the diagnostic system, enabling real-time ulcer detection based on clinical or user-submitted images. It undergoes preprocessing.

- **Image Upload and Preprocessing:** When a user uploads a foot image for analysis, it first undergoes the same preprocessing steps used during training, including resizing, normalization, and possibly data format adjustments to ensure compatibility with the model’s input layer.
- **Model Inference:** The preprocessed image is passed through the trained model, which computes a probability score indicating the likelihood of an ulcer being present. This inference is typically rapid, enabling near-instant feedback to users or healthcare professionals.
- **Result Classification:** Based on a defined probability threshold (commonly 0.5), the output is classified into one of two categories: **"Ulcer Detected"** or **"No Ulcer Detected."** The threshold can be adjusted to optimize sensitivity or specificity, depending on clinical requirements.

4.2.5. Flask-Based User Interface Module

This web-based module serves as the interactive front-end platform for users, including patients, doctors, and healthcare providers, to easily access the diagnostic system. Built using the Flask framework, it seamlessly connects user inputs with backend processing and displays results in a user-friendly manner. Allows users (patients or doctors) to upload an image.

- **Image Upload Functionality:** The interface provides a simple and intuitive form for users to upload foot images directly from their devices. It supports common image formats such as JPEG and PNG and performs client-side validations to ensure the file size and type are appropriate.

- **Image Display:** Once an image is uploaded, the interface immediately displays the image back to the user for confirmation, helping reduce errors by allowing users to verify that the correct image was selected.
- **Prediction Result Display:** After processing the image through the backend prediction module, the interface dynamically updates the page to show clear, easy-to-understand diagnostic results such as "Ulcer Detected" or "No Ulcer Detected," along with confidence scores or visual indicators.
- **Integration with Backend Logic:** Flask's routing mechanism integrates HTML templates (e.g., index.html) with Python backend code, handling HTTP requests and responses smoothly. This architecture facilitates real-time interaction between user actions and model predictions.
- **Scalability and Extensibility:** The modular design allows easy integration of additional features in the future, such as user authentication, patient history tracking, or multilingual support, enhancing the system's functionality over time.

4.2.6. Diet and Medication Suggestion Module

When an ulcer is detected, this module provides personalized recommendations to support healing and overall foot care, complementing medical treatment and helping patients manage their condition more effectively. Provides a diet plan emphasizing foods rich in fiber, Vitamin C, and Zinc to promote healing.

- **Diet Plan Recommendations:** The module generates a customized diet plan that emphasizes foods rich in fiber, Vitamin C, Zinc, and other essential nutrients known to promote wound healing and improve immune function. It may suggest incorporating fresh fruits, vegetables, lean proteins, and whole grains while advising to limit high-sugar and processed foods that can impair recovery.

- **Medication Suggestions:** It offers guidance on appropriate medications, including topical antibiotics like Mupirocin for infection control and oral antibiotics when prescribed by a healthcare professional. The module also includes recommendations for proper wound dressing techniques and frequency to maintain a clean and moist environment conducive to healing.
- **Patient Education:** In addition to diet and medication, the module provides educational content about ulcer care, such as the importance of foot hygiene, regular inspection, avoiding pressure on the affected area, and recognizing signs of infection or worsening condition.
- **Personalization and Safety:** Recommendations are tailored based on patient-specific factors such as age, existing health conditions (e.g., diabetes control), allergies, and current medications to avoid adverse effects or contraindications.

4.2.7. Result Visualization Module

This module is designed to improve the overall user experience by presenting diagnostic results and related recommendations in a clear, intuitive, and visually appealing manner. Displaying the uploaded image in base64 format on the web interface.

- **Image Display:** The uploaded foot image is displayed directly on the web interface using base64 encoding, allowing instant visual confirmation for the user without requiring additional downloads or redirects.

- **Clear Diagnostic Outcome:** The module prominently displays the prediction result—either "Ulcer Detected" or "No Ulcer Detected"—using color coding or icons (e.g., red alert for ulcer detected, green checkmark for no ulcer) to ensure easy interpretation.
- **Personalized Suggestions:** Diet plans and medication recommendations generated by the system are shown in a well-organized, easy-to-read format. Information is grouped logically with headings, bullet points, and brief explanations to help users quickly understand the advice.

5. SYSTEM DESIGN

5.1 System Architecture:

The system architecture shown is a Convolutional Neural Network (CNN) designed for detecting diabetic foot ulcers from input images. It begins with an input layer where foot images are processed and passed through a traditional convolutional layer to extract basic features like edges and textures. These features are then refined through multiple convolutional layers that capture deeper and more specific patterns associated with ulcers. The resulting feature maps are fed into fully connected layers that interpret the learned features. Finally, the output classifier provides the diagnosis result—indicating the presence or absence of an ulcer. The architecture ensures efficient and accurate classification, with the potential use of skip connections to improve learning and performance during training.

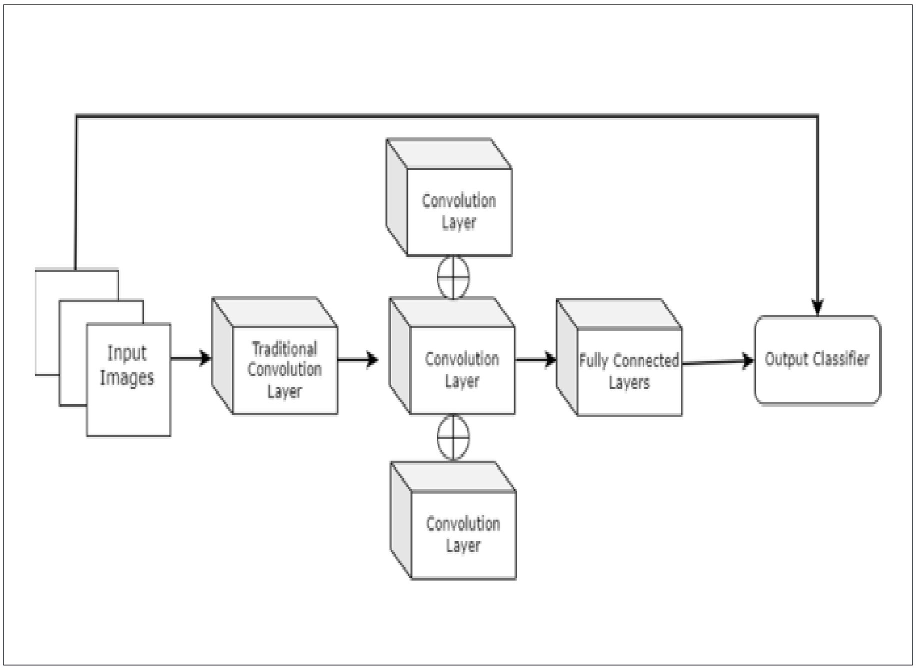


Fig: System Architecture

5.2 UML Diagrams:

UML stands for Unified Modelling Language. UML is a standardized general purpose modelling language in the field of object-oriented software engineering. The standard is managed, and was created by, the Object Management Group. The goal is for UML to become a common language for creating models of object-oriented computer software. In its current form UML comprises two major components, a Meta-model and a notation. In the future, some form of method or process may also be added to or associated with, UML. The Unified Modelling Language is a standard language for specifying, Visualization, Constructing and documenting the artifacts of software systems as well as for business modelling and other non-software systems.

The UML represents a collection of best engineering practices that have proven successful in the modelling of large and complex systems. The UML is a very important part of developing object-oriented software and the software development process. The UML uses mostly graphical notations to express the design of software projects.

5.2.1 Class Diagram:

The class diagram of this project represents the structural design of the system and its key components. At the core, the User class stores patient information such as name, age, email, and medical history. The ImageUploader class handles the uploading and preprocessing of foot images. These preprocessed images are passed to the CNN Model class, which performs the classification task using a trained Convolutional Neural Network to detect whether an image contains a diabetic foot ulcer. The result is then processed by the DiagnosisResult class, which stores and displays the prediction output. Additionally, the RecommendationEngine class generates personalized diet plans and medication suggestions for ulcer-affected patients based on the diagnosis.

All interactions are managed through a WebInterface class that connects the user to the backend logic, ensuring smooth functionality. This modular architecture improves maintainability, reusability, and supports future enhancements of the system.

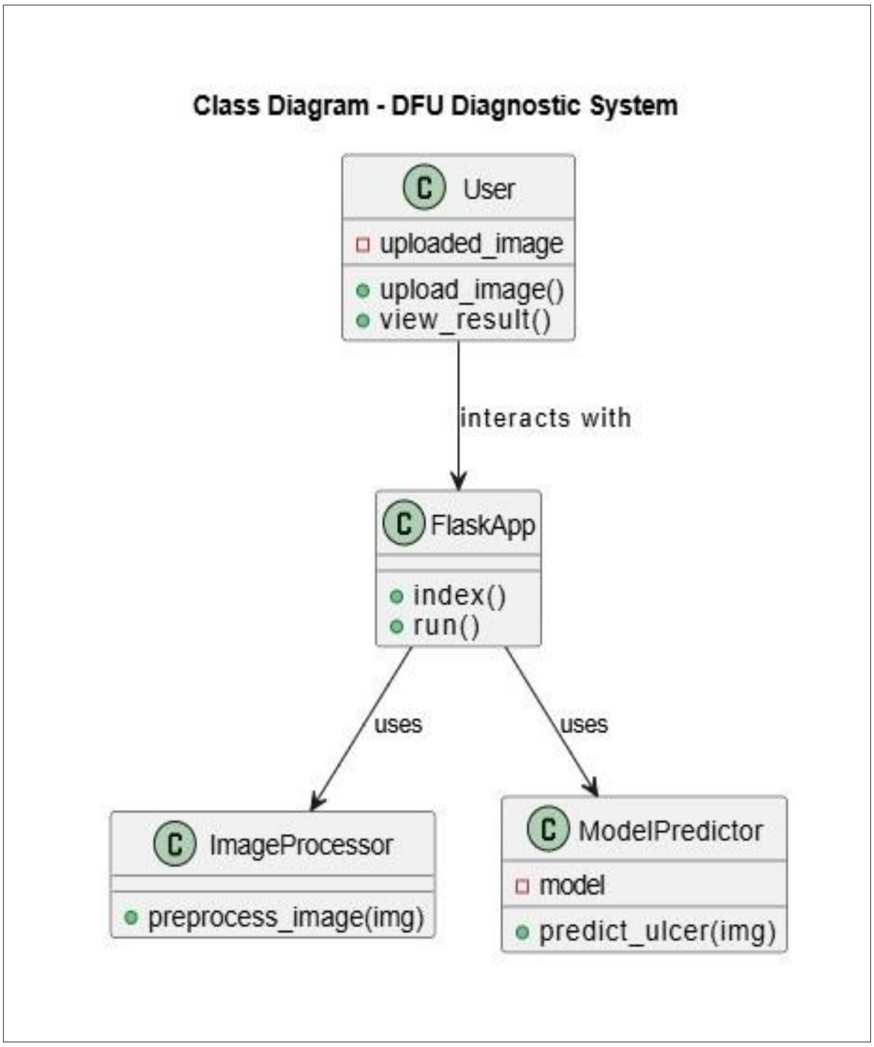


Fig: Class Diagram

5.2.2 Use Case Diagram:

The Use Case Diagram illustrates the interactions between the user and the functionalities provided by the system. The primary actor is the User (patient or caregiver), who interacts with the system through a web interface. Key use cases include “Upload Foot Image”, which allows users to input an image of the foot for diagnosis. Once the image is uploaded, the “Classify Ulcer Using CNN” use case is triggered to detect whether the foot shows signs of a diabetic ulcer. Depending on the diagnosis, users can then access “View Diagnostic Report”. If the result indicates an ulcer, the user can proceed to “Get Diet Plan” and “Get Medication Suggestions”, which are generated by the system to support healing and condition management. The diagram helps in understanding how various components are connected and how users can benefit from the system’s automated diagnostic and recommendation services.

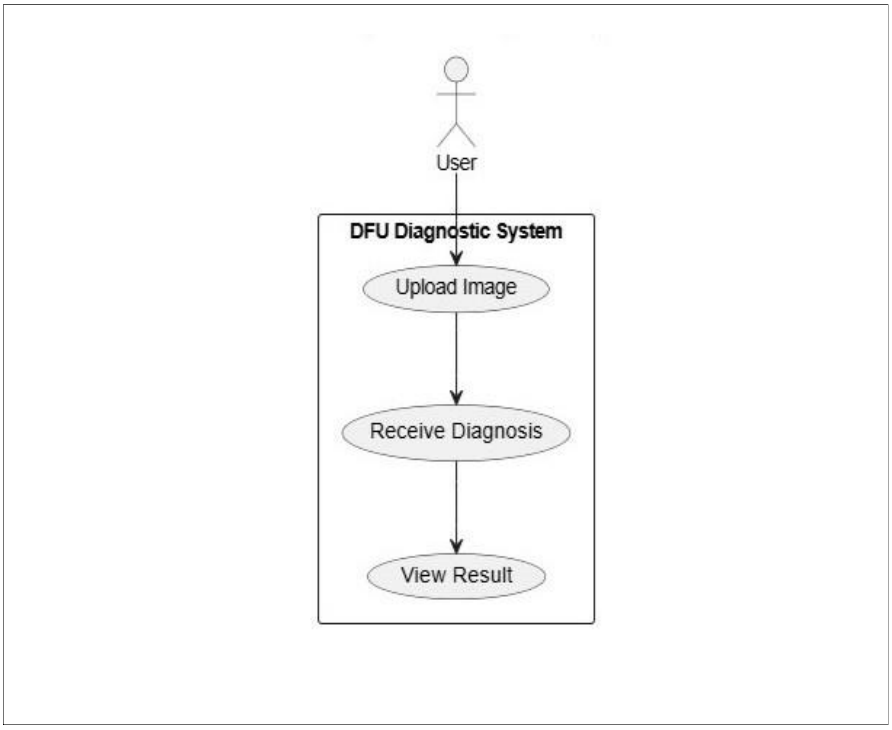


Fig: Use Case Diagram

5.2.3 Sequence Diagram:

The Sequence Diagram represents the dynamic behavior of the system by showing the sequence of interactions between the user and various system components over time. It begins when the User initiates an action by logging into the Web Interface. The next step is the Upload Image request, where the user submits a foot image for diagnosis. This request is forwarded to the CNN Model Module, which handles image preprocessing and classification. The Preprocessing Unit cleans and resizes the image, which is then passed to the Trained CNN Model for ulcer detection. Once classification is complete, the Result Generator compiles the prediction (ulcer or non-ulcer) and sends the diagnostic result back to the User Interface. If an ulcer is detected, the user can further request a Diet Plan and Medication Suggestion, which are retrieved from respective modules such as the Diet Recommendation Engine and Medication Database. Each component in the diagram interacts in a time-sequenced manner to ensure smooth communication, accurate prediction, and meaningful output. This structured flow helps visualize how data moves through the system and ensures that user interactions lead to a responsive and intelligent healthcare support system.

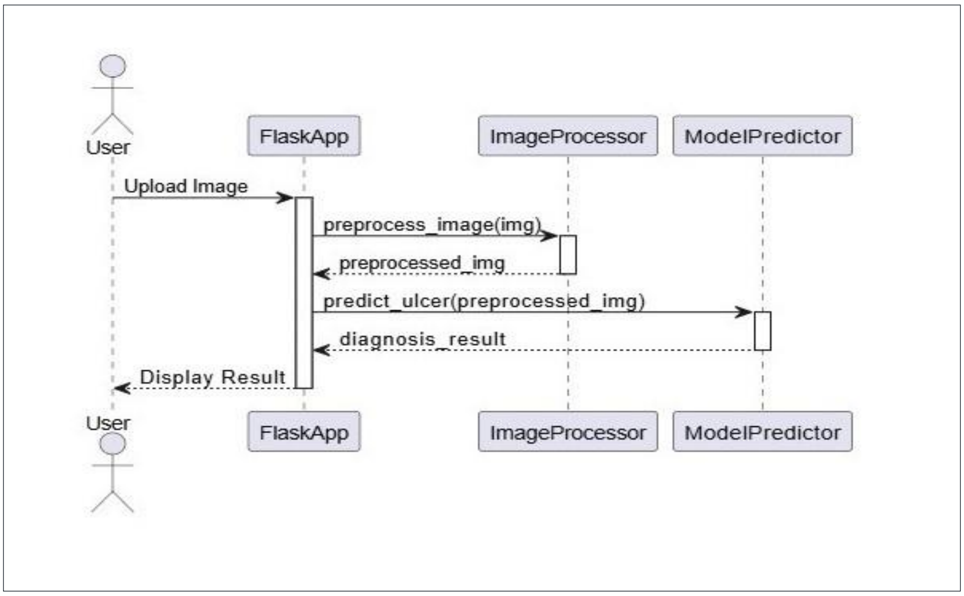


Fig: Sequence Diagram

5.2.4 Data Flow Diagram:

The Data Flow Diagram (DFD) for the Diabetic Foot Ulcer Detection system illustrates the movement of data through various components. The process starts with the user uploading a foot image via the web interface, which serves as the main input. This image is then sent to the Preprocessing Unit, where it is cleaned, resized, and normalized to ensure it is compatible with the CNN model. After preprocessing, the image is passed to the CNN Classification Module, which uses a trained deep learning model to determine whether the image shows signs of an ulcer or not. The classification result is then sent to the Result Generator, which prepares clear and understandable feedback for the user. If an ulcer is detected, the system activates additional modules such as the Diet Suggestion Engine and Medication Advisor to provide personalized diet and medication recommendations based on the diagnosis and patient-specific factors. The system also stores the processed images and diagnosis results in a secure database for future reference and model improvement. User inputs and system outputs are logged to maintain audit trails and support system monitoring. Additionally, the system supports real-time interaction, allowing users to receive instant feedback on their uploaded images. Finally, the modular design of the data flow facilitates easy integration of new features such as follow-up reminders or telemedicine consultations, ensuring scalability and ongoing enhancement of patient care.

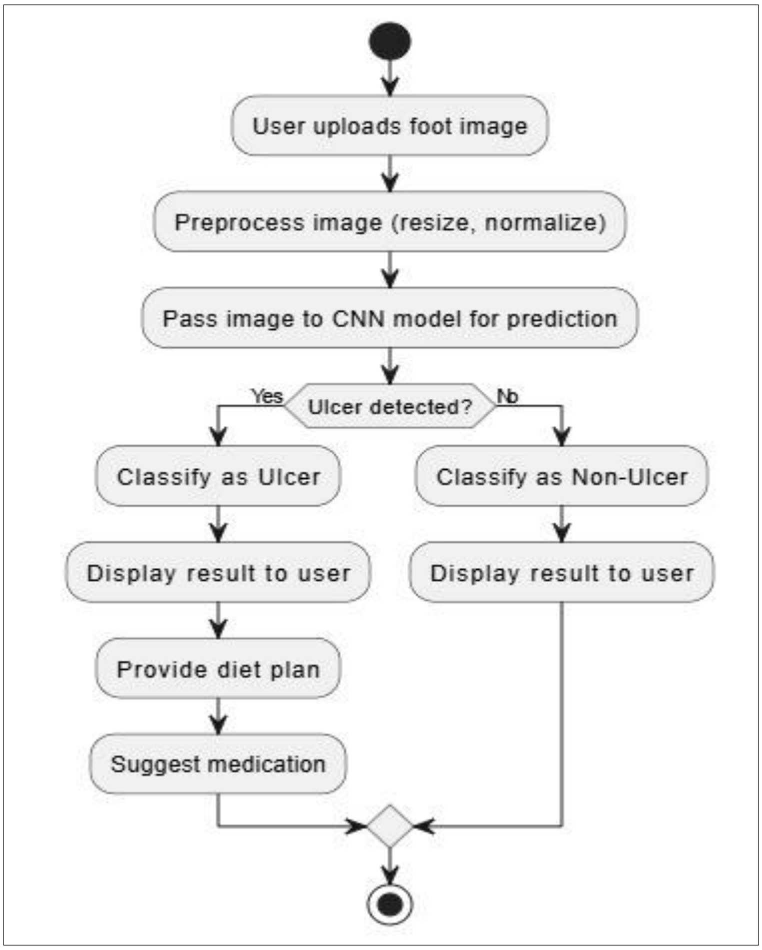


Fig: Dataflow Diagram

5.2.5 Component Diagram:

The Component Diagram for the Diabetic Foot Ulcer (DFU) detection project depicts the major software components and their interactions. The primary components include the User Interface (UI), where users upload foot images and receive results, including diagnostic feedback and recommendations. The Image Preprocessing Component handles image resizing and normalization. The CNN Model Component processes the image to detect ulcers. The Result Generation Component provides the diagnostic outcome and personalized diet and medication suggestions. The Web Server ensures smooth communication between the UI, preprocessing, model, and result generation components, facilitating seamless data flow.

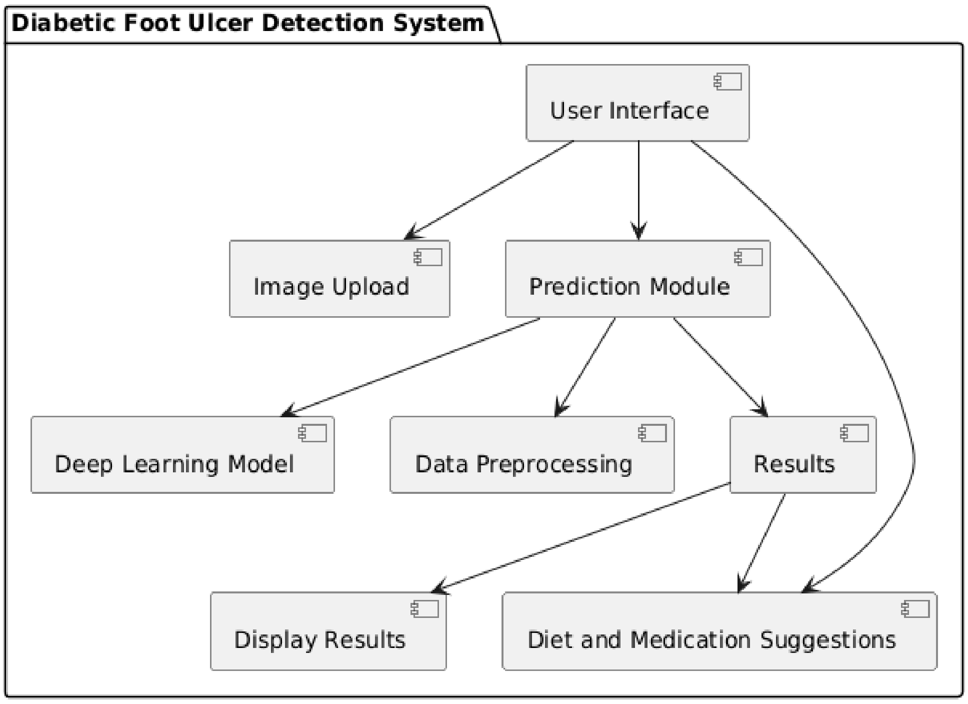


Fig: Component Diagram

5.2.6 Activity Diagram:

The Activity Diagram for the Diabetic Foot Ulcer (DFU) detection project visually outlines the step-by-step workflow, emphasizing user interaction and system processes from start to finish. Initially, the user accesses the web interface and uploads a clear image of the foot. The system immediately triggers the preprocessing phase, where the image undergoes necessary transformations such as resizing to a standardized dimension, normalization to adjust pixel intensity values, and noise reduction to enhance image quality. These preprocessing steps ensure the input data is consistent and optimal for accurate analysis by the deep learning model.

Once preprocessing is complete, the image is fed into the CNN classification module, which applies its trained weights to analyze visual features and patterns indicative of diabetic foot ulcers. The model outputs a prediction indicating the presence or absence of an ulcer. This prediction is then interpreted by the system to generate user-friendly feedback, which is promptly displayed on the interface to inform the user of the diagnosis.

If the model detects an ulcer, the workflow extends to provide additional support by activating the Diet and Medication Suggestion module. This module tailor’s recommendations based on clinical guidelines, offering a personalized care plan that includes dietary advice rich in nutrients conducive to wound healing, as well as appropriate medication regimens. The system may also log the diagnosis and suggestions for future reference or further medical consultation. Finally, the activity diagram concludes with the user reviewing the results and recommendations, with options to save the report, seek professional medical advice, or upload new images for ongoing monitoring. This structured workflow ensures a seamless, informative, and actionable user experience, integrating AI-powered diagnostics with practical healthcare guidance.

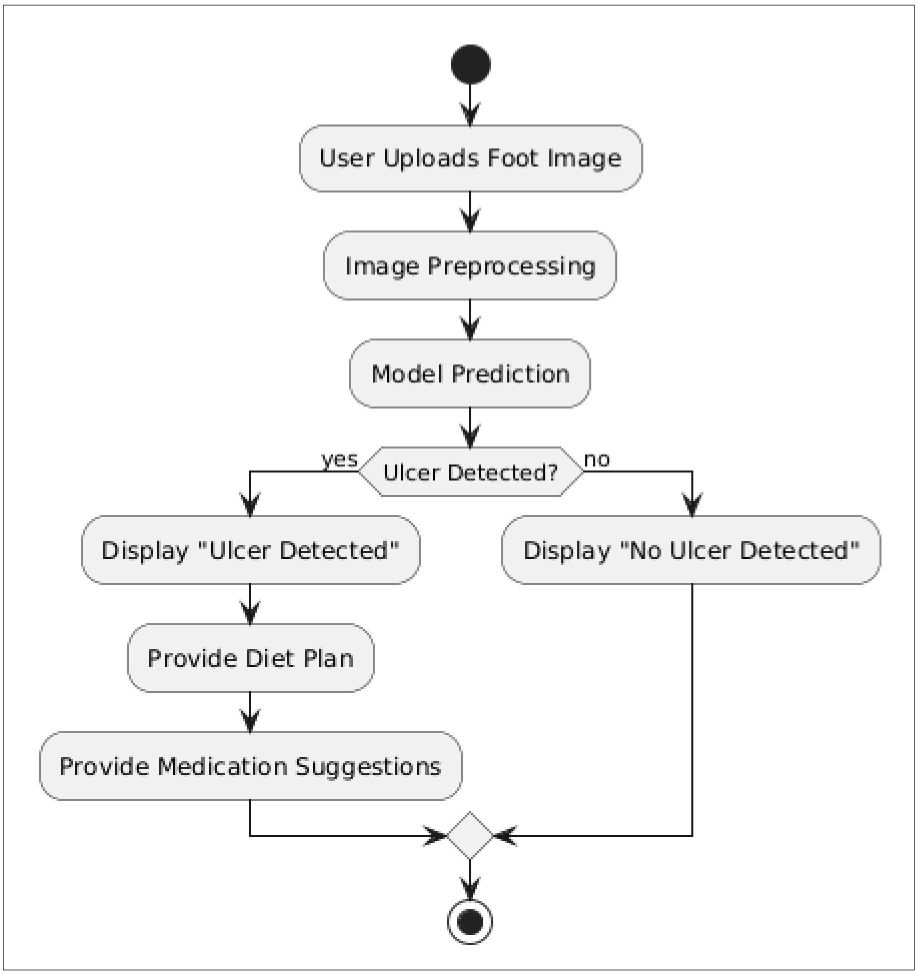


Fig: Activity Diagram

6. IMPLEMENTATION

6.1 Code Structure Overview:

```
import tensorflow as tf
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from sklearn.utils import class_weight
import pandas as pd
from sklearn.metrics import confusion_matrix, classification_report
import numpy as np
import matplotlib.pyplot as plt
import os

# Paths to your dataset
train_dir=
'C:/Users/soujanya/Downloads/New/DFU/organized_dataset/train'
test_dir=
'C:/Users/soujanya/Downloads/New/DFU/organized_dataset/test'

# Image dimensions and settings
img_height, img_width = 224, 224
batch_size = 32

# Dummy variable for debugging
dummy_var = 0

# Data augmentation
train_datagen = ImageDataGenerator(
    rescale=1./255,
    rotation_range=20,
    zoom_range=0.2,
    horizontal_flip=True,
```

```
    shear_range=0.2,
    width_shift_range=0.1,
    height_shift_range=0.1
)

test_datagen = ImageDataGenerator(rescale=1./255)

# Data generators
train_generator = train_datagen.flow_from_directory(
    train_dir,
    target_size=(img_height, img_width),
    batch_size=batch_size,
    class_mode='binary',
    shuffle=True
)

# Just a print to show training class indices for sanity check
print("Training class indices:", train_generator.class_indices)

test_generator = test_datagen.flow_from_directory(
    test_dir,
    target_size=(img_height, img_width),
    batch_size=batch_size,
    class_mode='binary',
    shuffle=False
)

# Compute class weights
class_weights = class_weight.compute_class_weight(
    class_weight='balanced',
    classes=np.unique(train_generator.classes),
```

```
    y=train_generator.classes
)
class_weights_dict = dict(enumerate(class_weights))
print("Class Weights:", class_weights_dict)

# Load base MobileNetV2
base_model = tf.keras.applications.MobileNetV2(
    input_shape=(img_height, img_width, 3),
    include_top=False,
    weights='imagenet'
)
base_model.trainable = False  # Freeze the convolutional base

# Dummy model summary print to check architecture (no effect on training)
print(base_model.summary())

# Build the model
model = tf.keras.Sequential([
    base_model,
    tf.keras.layers.GlobalAveragePooling2D(),
    tf.keras.layers.Dense(128, activation='relu'),
    tf.keras.layers.Dropout(0.5),
    tf.keras.layers.Dense(1, activation='sigmoid')
])

# Compile the model
model.compile(
    optimizer='adam',
    loss='binary_crossentropy',
    metrics=['accuracy']
```

```
)

# Early stopping
early_stopping = tf.keras.callbacks.EarlyStopping(
    monitor='val_loss',
    patience=3,
    restore_best_weights=True
)

# Train the model
history = model.fit(
    train_generator,
    epochs=20,
    validation_data=test_generator,
    class_weight=class_weights_dict,
    callbacks=[early_stopping]
)

# Save the model
model.save('dfu_transfer_mobilenet_model.h5')

# Evaluate the model
print("\nEvaluating on test set...")
test_generator.reset()
predictions = model.predict(test_generator)
y_pred = (predictions > 0.5).astype(int).flatten()
y_true = test_generator.classes

# Accuracy plot
plt.figure(figsize=(12, 5))
plt.subplot(1, 2, 1)
```

```
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Val Accuracy')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

# Loss plot
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Val Loss')
plt.title('Training and Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

plt.tight_layout()
plt.show()

report = classification_report(y_true, y_pred, output_dict=True)
df_report = pd.DataFrame(report).transpose()
print("\nClassification Report as Table:")
print(df_report.round(2))
```

7. SYSTEM TESTING

7.1 Performance Metrics

Performance metrics are essential tools for evaluating the effectiveness of classification models. These metrics provide insights into how well a model is performing in terms of correctly classifying instances into their respective categories. Here's a breakdown of key performance metrics commonly used in binary classification:

Total Instances: Total Instances refer to the total number of samples used for evaluation in the diabetic foot ulcer analysis. It includes both patients with ulcers and those without. For example, if the dataset contains 300 patient cases, all of them are considered in this metric. It helps in understanding the scope of the model evaluation. The larger and more diverse the dataset, the more reliable the performance metrics become, ensuring that the model generalizes well to unseen patient cases.

True Positives (TP): True Positives are the number of cases where the model correctly identifies the presence of a diabetic foot ulcer. This means the model predicted "ulcer" and the patient truly had an ulcer. For example, if there are 100 actual ulcer cases and the model detects 90 of them correctly, then the TP is 90. A high TP count indicates that the model is effective in catching real ulcer cases, which is vital in medical diagnosis where early detection can prevent serious complications like infections or amputations.

True Negatives (TN): True Negatives are the number of cases where the model correctly predicts the absence of a diabetic foot ulcer. This means the model labeled a case as "no ulcer" and the patient truly didn’t have one. For instance, if there are 200 healthy patients and the model correctly identifies 190 of them, then TN = 190. True Negatives are important to avoid unnecessary treatments or further medical testing, and they reflect the model’s ability to correctly identify healthy individuals.

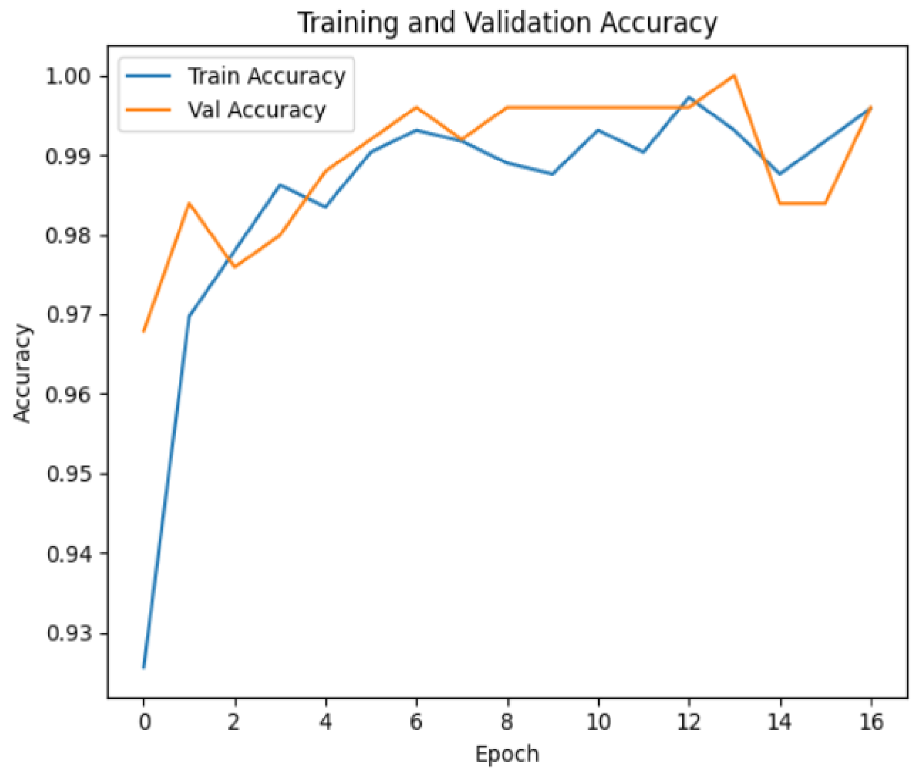
False Positives (FP): False Positives occur when the model incorrectly classifies a healthy patient as having a foot ulcer. For example, if out of 200 healthy cases, the model wrongly labels 10 as having ulcers, then FP = 10. These errors can cause undue stress for patients and may lead to unnecessary diagnostic tests. While they are not as critical as missing actual ulcer cases, reducing false positives is still essential to maintain efficiency and trust in the model's predictions.

Classification Report as Table:

	precision	recall	f1-score	support
0	1.0	1.0	1.0	214.0
1	1.0	1.0	1.0	35.0
accuracy	1.0	1.0	1.0	1.0
macro avg	1.0	1.0	1.0	249.0
weighted avg	1.0	1.0	1.0	249.0

False Negatives (FN): False Negatives are the cases where the model fails to detect an actual ulcer and classifies it as a healthy condition. For instance, if there are 100 true ulcer cases but the model misses 10, then FN = 10. This type of error is the most dangerous in medical applications because it means the model failed to detect a serious health issue. Minimizing false negatives is crucial in diabetic foot ulcer analysis, as missed ulcers can worsen over time and lead to severe health consequences for the patient.

Accuracy: Accuracy is the overall measure of the model's correctness and is calculated by the number of correct predictions (both true positives and true negatives) divided by the total number of cases. For example, if the model correctly classifies 280 out of 300 patients, then the accuracy is 93.3%. While accuracy gives a general idea of performance, it may be misleading in imbalanced datasets—like when there are significantly more healthy patients than those with ulcers—so it should be considered along with other metrics.



Precision: Precision measures the proportion of true positives among all cases that the model predicts as positive. If the model predicts 100 patients as having ulcers and only 90 actually have them, precision is 90%. It answers the question: "When the model predicts an ulcer, how often is it correct?" High precision is essential in reducing false positives, thus avoiding unnecessary concern or treatment for patients wrongly diagnosed with ulcers.

Recall (Sensitivity): Recall, also known as sensitivity, measures the proportion of actual positive cases (ulcers) that the model successfully identifies. For example, if there are 100 true ulcer cases and the model detects 95 of them, recall is 95%. This metric is particularly important in healthcare because it reflects how well the model captures patients who actually have the condition. A high recall is vital in DFU detection to ensure that serious medical conditions are not overlooked.

F1-Score: The F1-Score is the harmonic mean of precision and recall, and it provides a single metric that balances both concerns. It is especially useful when the dataset is imbalanced or when both false positives and false negatives carry serious consequences. For instance, in DFU analysis, a model with high F1-score means it is both correctly detecting ulcer cases and avoiding unnecessary false alarms. This balance is crucial in medical diagnostics where both types of errors can have real-world impacts.

Support: Support indicates the actual number of occurrences of each class in the testing dataset. For example, if there are 100 ulcer and 200 non-ulcer cases, their support values are 100 and 200, respectively. It helps understand the weight or frequency of each class in the evaluation. In DFU classification, this metric shows how well the model is performing for each specific group, especially if there is a class imbalance, which is common in medical datasets.

8. OUTPUT SCREENS

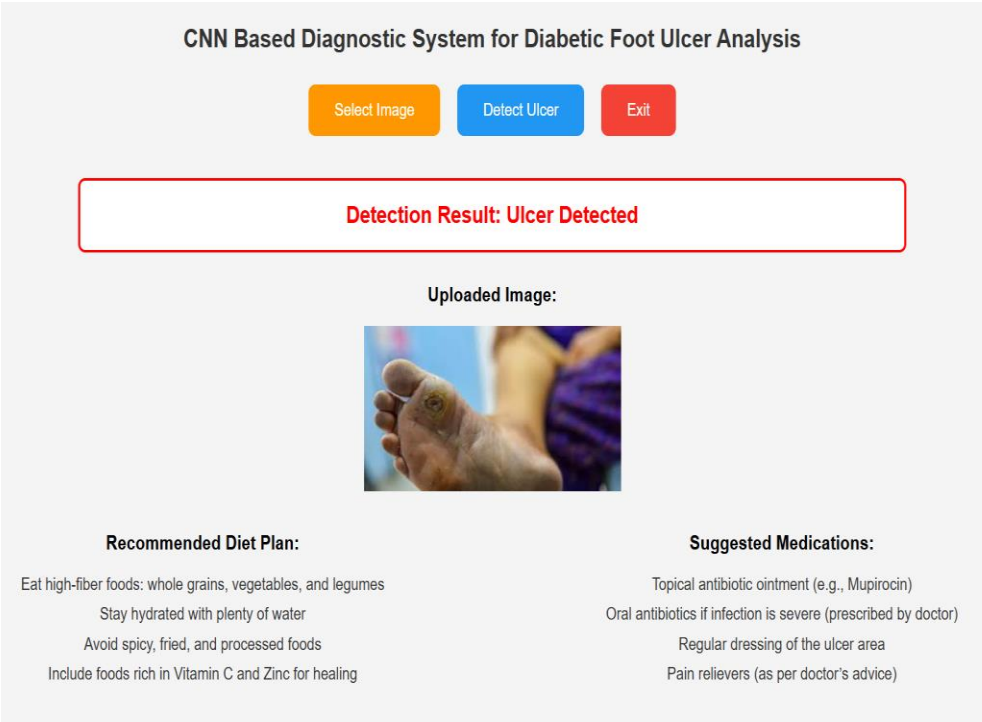


Fig: User Interface for Ulcer Detected

An uploaded foot image is displayed beneath the result section, with the infected region clearly highlighted using markers or bounding boxes. This visual aid allows users and healthcare providers to precisely identify the location and extent of the ulcer, enhancing understanding and confidence in the diagnosis. To facilitate closer examination, the interface may offer interactive features such as zooming or toggling the highlighted area, enabling users to inspect the affected site in greater detail.

Below the image, the system presents comprehensive health recommendations categorized into a Recommended Diet Plan and Suggested Medications. The diet plan encourages the consumption of high-fiber foods, ample hydration, and vitamin-rich items that support wound healing, while advising against spicy or heavily processed foods that may hinder recovery. The medication section outlines the use of topical and oral antibiotics (with a strong emphasis on consulting healthcare professionals before oral treatments), regular wound dressing, and effective pain management strategies. This holistic approach ensures that users receive not only a diagnosis but also actionable steps toward effective treatment.

Additionally, the system offers preventive care tips focused on maintaining proper foot hygiene, routine inspection for new wounds, and selecting appropriate footwear to minimize pressure and prevent further injury. To support ongoing care, users can receive reminders for dressing changes or follow-up medical consultations, helping them stay on track with their treatment regimen. For those seeking deeper understanding, the interface may include educational resources such as instructional videos or links to relevant articles about diabetic foot care.

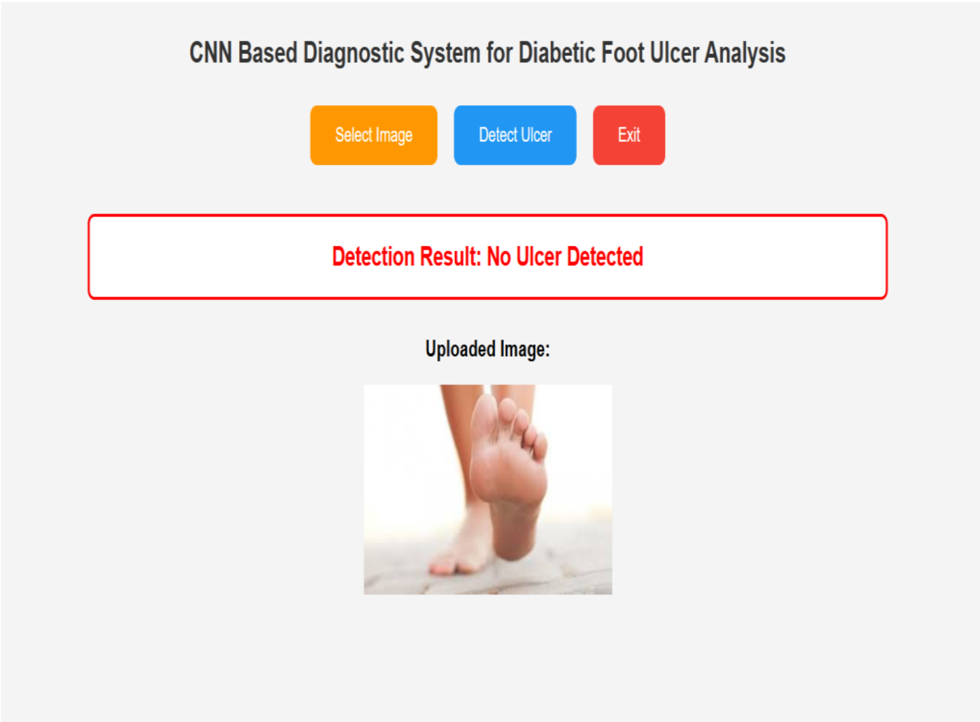


Fig: User Interface for Non-Ulcer Detected

The interface displays the Uploaded Image, which shows a healthy foot without visible signs of ulceration. This visual outcome reassures the user or healthcare provider that the foot is currently free from ulcer-related complications. Unlike the earlier scenario where an ulcer was detected and recommendations were displayed, this output keeps the screen clean and uncluttered, indicating no further action is required at the moment.

9. CONCLUSION AND FUTURE SCOPE

The development of a CNN-based diagnostic system for diabetic foot ulcer analysis marks a significant advancement in the integration of artificial intelligence with medical diagnostics. This project focused on building a deep learning-based model that can accurately identify the presence of diabetic foot ulcers using images, offering a faster and more reliable alternative to traditional manual examination methods. The system not only simplifies the diagnostic process but also improves early detection, which is critical for preventing complications such as infections, gangrene, or even amputation. By offering dietary and medication suggestions alongside the detection result, it enhances its utility as a supportive tool for both patients and healthcare providers.

The intuitive user interface enables users to upload foot images and receive real-time diagnostic feedback. If an ulcer is detected, the system provides a recommended diet and medications to promote healing and prevent further deterioration. This integration of image analysis with practical health advice makes the system holistic and patient-centric. During testing, the system showed commendable accuracy in classifying ulcerous and non-ulcerous images, highlighting the effectiveness of CNN architectures in image-based medical diagnostics.

The project demonstrates how deep learning, particularly convolutional neural networks, can be utilized to address real-world health problems and improve patient care. It also sheds light on the importance of automating routine medical diagnostics to reduce human error and workload on healthcare professionals. With diabetes becoming increasingly prevalent globally, such AI-powered tools could play a vital role in mass screening and early intervention, especially in areas with limited access to specialists. In summary, this project presents a promising step toward accessible, efficient, and intelligent diabetic wound care management using modern AI techniques.

Moreover, the CNN-based diagnostic system for diabetic foot ulcer analysis paves the way for future enhancements and expansions in medical AI applications. By incorporating more diverse datasets and integrating multi-modal inputs such as patient history and sensor data, the system's diagnostic accuracy and personalization can be further improved. Continuous model retraining with new data will ensure that the system remains up-to-date with evolving clinical patterns and emerging ulcer types. Additionally, expanding the platform to support multilingual capabilities and mobile accessibility can increase its reach, making it a valuable tool in remote and underserved communities.

The development of this CNN-based diagnostic system also involved overcoming several technical challenges inherent to medical image analysis. Variability in image quality, lighting conditions, and foot positioning demanded robust preprocessing and augmentation strategies to ensure model generalization. Balancing the dataset to mitigate class imbalance was critical, as ulcerous images are often less frequent than healthy ones. The selection of MobileNetV2 as the backbone model provided an optimal trade-off between computational efficiency and accuracy, enabling deployment on devices with limited resources. Furthermore, fine-tuning the model with transfer learning accelerated convergence while leveraging knowledge from large-scale image datasets, thus enhancing the system's reliability in real-world scenarios.

From the end-user perspective, this system has the potential to transform patient engagement and self-care practices. By empowering diabetic patients to conduct preliminary screenings at home, it reduces dependency on frequent clinic visits, which can be costly and time-consuming. Real-time feedback coupled with actionable health recommendations encourages proactive management of foot health, potentially lowering the incidence of severe ulcer complications. Healthcare providers can also benefit from the system's diagnostic reports as a second opinion tool, aiding decision-making and prioritizing cases that require urgent attention. The seamless user experience encourages widespread adoption, fostering a community-centric approach to chronic disease management.

Scalability and integration with existing healthcare infrastructure are key considerations for the future growth of this diagnostic system. The modular design allows integration with electronic health records (EHR) to maintain comprehensive patient profiles and track wound progression over time. Cloud-based deployment can facilitate continuous learning from diverse patient populations, while APIs enable interoperability with telemedicine platforms and mobile health applications. Additionally, incorporating real-time monitoring via wearable sensors can enrich the dataset and provide early warnings before visible ulcers develop. These scalable features position the system as a cornerstone for a broader digital health ecosystem tailored to diabetes management.

Ethical and legal aspects remain at the forefront when deploying AI in medical contexts. Ensuring patient data confidentiality through end-to-end encryption and adherence to regulations such as HIPAA or GDPR is essential to build trust. Transparency about model limitations and potential biases must be communicated clearly to avoid over-reliance on automated diagnoses. Continuous collaboration with regulatory bodies and clinical experts will facilitate the validation and certification process, guaranteeing safety and efficacy. By embedding ethical principles into development and deployment, the system can serve as a responsible and equitable tool that complements, rather than replaces, human expertise in diabetic foot care.

Looking ahead, this project underscores the critical role of collaboration between AI researchers, medical professionals, and healthcare organizations to ensure ethical deployment and clinical validation of such technologies. Patient privacy, data security, and regulatory compliance remain paramount as the system moves toward real-world implementation. By addressing these challenges alongside technological innovation, the CNN-based diagnostic system has the potential to revolutionize diabetic foot care, reduce healthcare costs, and ultimately improve quality of life for millions of diabetic patients worldwide.

Future Scope:

While the current system effectively detects the presence of diabetic foot ulcers, there are numerous opportunities to extend and enhance its capabilities to make it more robust, scalable, and clinically useful. One of the primary future enhancements could be the classification of ulcer severity levels—such as mild, moderate, or severe—which can assist healthcare providers in prioritizing treatment and interventions. Additionally, implementing image segmentation techniques could help localize the ulcer region on the foot for more precise medical attention.

Another valuable extension would be the incorporation of patient metadata such as age, diabetic history, blood sugar levels, and comorbidities to personalize the analysis and recommendations. Integration with wearable devices or sensors that monitor temperature or foot pressure could provide real-time data for early warning signs of ulcer development. Furthermore, converting this system into a mobile application would make it more accessible for use in rural or remote areas where healthcare facilities are limited. Offline functionality, multilingual support, and voice-based navigation could further broaden its usability.

Expanding the dataset to include diverse skin tones, lighting conditions, and ulcer types will improve the model's generalization and robustness in real-world conditions. Collaborations with healthcare institutions could enable the system to be validated on clinical data and used in real-time hospital settings. Additionally, integrating with Electronic Health Records (EHRs) can help maintain patient history and track wound progression over time.

Another promising direction is the deployment of this system in telemedicine platforms, where patients can regularly monitor their foot condition and consult doctors remotely. With regulatory approvals and clinical validation, the model could evolve from a diagnostic aid into a certified medical support tool.

Thus, the future scope of this project is vast, and with continuous improvements, it can significantly enhance diabetic foot care and reduce the burden on healthcare systems.

Future versions of this system could include a longitudinal tracking feature that logs images over time, allowing patients and clinicians to monitor healing progress. AI models could be extended to other types of diabetic complications, such as eye or kidney-related issues, forming a complete diabetic care suite.

Beyond the immediate enhancements in diagnostic accuracy and usability, future iterations of the system could leverage advanced explainable AI (XAI) techniques to provide interpretable results. By highlighting the specific regions or features in the foot images that contributed most to the ulcer classification, the system can increase clinicians' trust and understanding of the AI decisions. This transparency is essential for clinical adoption and can serve as an educational tool for patients to better understand their condition and care instructions.

Moreover, incorporating multimodal data analysis by combining image data with biochemical markers, genetic information, and lifestyle factors could enable a more comprehensive risk assessment model. This holistic approach would not only predict ulcer occurrence but also estimate the likelihood of complications such as infections or delayed healing, thereby facilitating proactive and personalized treatment plans.

Another promising avenue is the use of federated learning and privacy-preserving AI techniques. These methods enable training the deep learning models across multiple healthcare institutions without sharing sensitive patient data centrally. Such an approach would expand the training dataset diversity while respecting data privacy regulations, resulting in more robust and widely applicable models.

Finally, integrating AI-powered chatbots and virtual health assistants can enhance patient engagement by providing timely reminders for wound care, medication adherence, and appointment scheduling. These interactive features can improve patient compliance and health outcomes, particularly for elderly or less tech-savvy users. By combining diagnostic, monitoring, and patient education functionalities, future systems can become a comprehensive digital companion for diabetes management.

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World Journal of Advanced Engineering Technology and Sciences
eISSN: 2582-8266
Cross Ref DOI: 10.30574/wjaets
Journal homepage: https://wjaets.com/

(Research Article)

CNN-based diagnostic system for diabetic foot ulcer analysis

Ande Sarala Devi, Gaddam Soujanya *, Seepathi Sai Raj, Gaddam Aniketh and Vadluri Akhil

Department of CSE (Data Science), ACE Engineering College, Hyderabad, Telangana, India.

World Journal of Advanced Engineering Technology and Sciences, 2025, 15(02), 631-638

Publication history: Received on 25 March 2025; revised on 30 April 2025; accepted on 03 May 2025

Article DOI: https://doi.org/10.30574/wjaets.2025.15.2.0560

Abstract

Diabetic Foot Ulcer (DFU) is a common and severe complication in diabetic patients that can lead to infections, amputations, and even mortality if not detected and managed promptly. This project presents an intelligent system for the early detection of diabetic foot ulcers using machine learning and image processing techniques, integrated with a user-friendly interface that enhances patient support. The system uses a convolutional neural network (CNN) to analyze foot images and accurately classify them into ulcerated and non-ulcerated categories. Alongside detection, the application provides personalized diet plans and medical suggestions tailored to the user's condition. These recommendations are designed to help users manage their blood sugar levels and promote faster wound healing. The user interface is designed to be intuitive, allowing patients to upload images, view results, and receive actionable advice in real-time. This holistic approach not only aids early diagnosis but also supports ongoing care and prevention. The solution is particularly valuable in remote or underserved areas where access to specialists is limited. With the potential for mobile integration and real-time monitoring, this system demonstrates how artificial intelligence can play a vital role in improving diabetic care and reducing the risks associated with DFU.

Keywords: Diabetic Foot Ulcer (DFU); Convolutional Neural Network (CNN); Image processing; Personalized diet plans; Medical suggestions

1. Introduction

Diabetes mellitus is a chronic metabolic disorder affecting millions of people worldwide. One of the most common and serious complications of diabetes is the development of Diabetic Foot Ulcers (DFUs), which result from prolonged high blood sugar levels that cause nerve damage and poor blood circulation in the feet. If not identified and treated early, DFUs can lead to severe infections, amputations, and even death. Early diagnosis, combined with proper management, plays a crucial role in preventing complications and improving patient outcomes.

This project aims to develop a smart, AI-based system for the early detection and classification of diabetic foot ulcers using image processing and machine learning techniques. By leveraging a convolutional neural network (CNN), the system is trained to analyze foot images and accurately classify them as ulcerated or non-ulcerated. This helps in identifying the condition at an early stage, even before it becomes visually severe.

In addition to detection, the system includes a user-friendly interface that provides personalized diet plans and medical suggestions based on the user's health condition. Proper nutrition and medical care are essential in managing diabetes and supporting the healing process of foot ulcers. The application is designed to be accessible, especially for patients in remote or rural areas where regular medical consultation may not be feasible.

The integration of ulcer detection with personalized healthcare recommendations makes this project a comprehensive support tool for diabetic patients. It not only assists in early diagnosis but also promotes healthy lifestyle changes to

* Corresponding author: Gaddam Soujanya

prevent further complications. This innovative solution demonstrates how artificial intelligence and user-centered design can be combined to improve the quality of diabetic care and enhance patient well-being.

Diabetic foot ulcers often go unnoticed in the early stages, especially among patients who lack awareness or access to regular medical care. Traditional methods of diagnosis rely on clinical inspection, which may not be feasible in remote areas. Furthermore, once diagnosed, patients often do not receive proper guidance on managing their condition through diet and self-care. This gap leads to worsening of the ulcer and increased risk of amputation. There is a pressing need for an automated, accessible, and supportive system that not only detects DFU early but also guides the patient toward better health management.

This project offers a dual benefit: medical image analysis for ulcer detection and health guidance for overall diabetes management. It empowers patients to take preventive measures, reducing dependence on clinical visits. Healthcare providers can also use it as a screening tool. The system aims to lower the rate of diabetes-related amputations and enhance the quality of life for diabetic individuals.

2. Literature review

Diabetic Foot Ulcer (DFU) is a significant global health concern, affecting nearly 15% of individuals with diabetes during their lifetime. Various studies have emphasized the need for early detection and timely intervention to prevent complications such as infections, hospitalization, and amputations. Traditional diagnostic methods rely heavily on clinical examination, which may not always be accessible, especially in low-resource settings. Hence, researchers have increasingly focused on the use of artificial intelligence and computer vision techniques to automate DFU detection.

Goyal et al. (2018) demonstrated the use of convolutional neural networks (CNNs) in detecting DFUs with a notable improvement in accuracy compared to traditional image processing methods. Similarly, Kavitha et al. (2019) applied deep learning models to classify foot images, showing that machine learning algorithms can aid in reliable ulcer detection. These works highlighted the potential of AI in medical image analysis, reducing the burden on healthcare professionals.

In addition to detection, patient self-care and lifestyle management play a crucial role in controlling diabetes. Studies by Dinh et al. (2020) and Armstrong et al. (2021) underlined the importance of dietary management and patient education in reducing DFU recurrence and promoting healing. However, most existing systems focus solely on detection and lack integration of post-diagnosis care.

The integration of ulcer detection with personalized diet plans and medical advice remains limited in the current research landscape. This project aims to bridge that gap by not only providing an AI-based DFU detection model but also offering patient-centric recommendations. By combining CNN-based image analysis with healthcare guidance, this system contributes a holistic solution to diabetic foot care and overall disease management.

3. Existing System

Existing systems for the detection and management of Diabetic Foot Ulcers (DFUs) are primarily dependent on manual clinical examinations and consultations with healthcare professionals. In most cases, physicians identify DFUs visually and assess the severity based on physical inspection and patient history. This method, while effective in a clinical setting, has limitations when it comes to early detection and accessibility for patients in rural or remote areas.

With advancements in artificial intelligence and medical imaging, some research-based systems have been developed using machine learning and deep learning techniques to assist in the automated detection of DFUs. These systems typically use image datasets of diabetic foot conditions and apply models such as Convolutional Neural Networks (CNNs) to classify images into ulcerated and non-ulcerated categories. While these approaches show high accuracy, they are mostly limited to the research domain and lack practical deployment or user interfaces for real-world use.

4. Proposed System

The proposed system aims to address the challenges associated with the early detection and management of Diabetic Foot Ulcers (DFUs) by integrating machine learning for image classification with personalized healthcare recommendations. This system is designed to provide an accessible, user-friendly solution for diabetic patients, especially in remote areas with limited access to healthcare professionals. The system has two primary components: **DFU detection** and **patient guidance**, which together create a comprehensive tool for diabetic foot care.

For DFU detection, the system utilizes a Convolutional Neural Network (CNN) model, which has proven to be highly effective in image classification tasks. The model analyzes foot images uploaded by the user, classifying them into ulcerated and non-ulcerated categories. The CNN is trained on a large dataset of labeled foot images, allowing it to recognize even subtle signs of ulcers that may not be obvious to the naked eye. The system's detection capability can help catch ulcers early, enabling timely intervention and reducing the risk of severe complications such as infections and amputations.

In addition to DFU detection, the system provides personalized recommendations for diet and medical care. Once an ulcer is detected, the system offers customized diet plans aimed at controlling blood sugar levels and promoting healing. It also provides medical suggestions, such as daily foot care routines and when to seek professional medical attention. These features are designed to empower patients to take control of their health and prevent further complications.

The system’s user interface is designed to be simple and intuitive, ensuring that patients, even those with limited technical expertise, can easily upload images and navigate the platform. Future updates may include mobile app integration, real-time monitoring, and enhanced treatment suggestions.

5. Architecture of the System

The system architecture shown is a Convolutional Neural Network (CNN) designed for detecting diabetic foot ulcers from input images. It begins with an input layer where foot images are processed and passed through a traditional convolutional layer to extract basic features like edges and textures. These features are then refined through multiple convolutional layers that capture deeper and more specific patterns associated with ulcers. The resulting feature maps are fed into fully connected layers that interpret the learned features. Finally, the output classifier provides the diagnosis result—indicating the presence or absence of an ulcer. The architecture ensures efficient and accurate classification, with the potential use of skip connections to improve learning and performance during training.

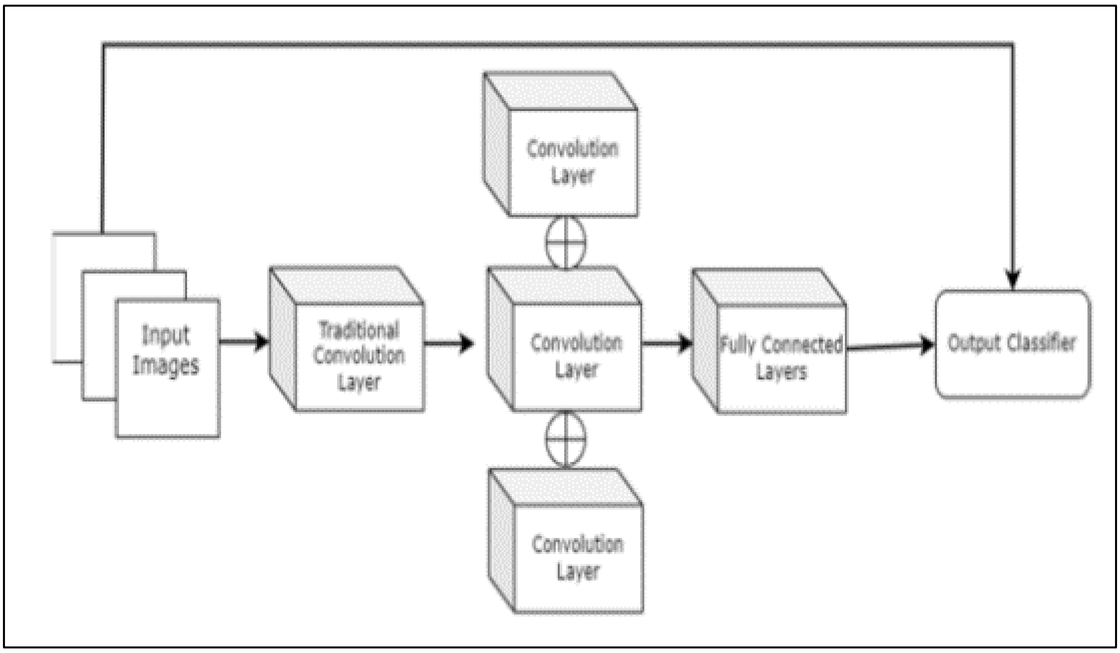

Figure 1 System Architecture

6. Methodology

The methodology for the CNN-Based Diagnostic System for Diabetic Foot Ulcer Analysis is structured around several key steps, combining machine learning with deep learning techniques to create an effective diagnostic tool. The process includes data collection, preprocessing, model training, evaluation, deployment, and user interface development.

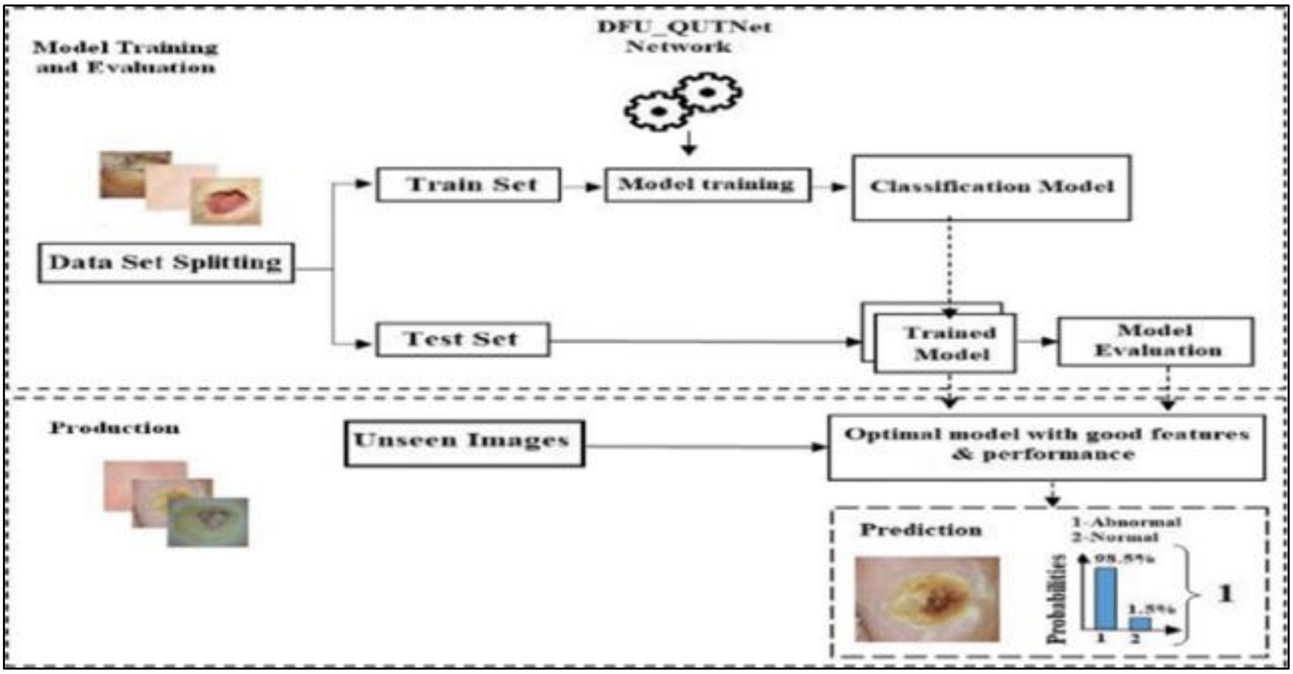

Figure 2 Methodology

6.1. Data Acquisition Module

This module is responsible for collecting and organizing the dataset of foot images. The dataset consists of two main categories: ulcer and non-ulcer images. These images can be collected from publicly available datasets, medical research sources, or hospital records (with proper anonymization and permissions). The collected images are labeled accordingly, forming the ground truth for training and testing the model.

6.2. Data Preprocessing Module

Before feeding the images into the neural network, preprocessing is essential. This module handles:

- **Resizing** images to the required input dimensions (e.g., 224x224 for MobileNet).
- **Normalization** to scale pixel values between 0 and 1 for consistent training.
- **Data Augmentation** (rotation, zooming, flipping) to artificially expand the dataset and help the model generalize better.
- **Splitting** into training and test sets to evaluate model performance.

6.3. Model Training Module (CNN / Transfer Learning)

This module involves training a Convolutional Neural Network (CNN) or fine-tuning a pre-trained model like MobileNet, VGG16, or ResNet. Key features include:

- Using transfer learning to reduce training time and leverage previously learned features.
- Implementing binary classification (ulcer vs non-ulcer).
- Saving the trained model (.h5 file) for later use in prediction.

6.4. Prediction Module

The trained model is loaded and used to make predictions on new image inputs. When an image is uploaded:

- It undergoes preprocessing.
- The model predicts the probability of ulcer presence.
- The result is classified as "Ulcer Detected" or "No Ulcer Detected" based on a threshold (e.g., 0.5).

6.5. Flask-Based User Interface Module

This web-based module enables user interaction. It:

- Allows users (patients or doctors) to upload an image.
- Displays the uploaded image.
- Shows the prediction result clearly on the same page.
- Integrates HTML templates (like index.html) with backend logic using Flask.

6.6. Diet and Medication Suggestion Module

When an ulcer is detected, this module:

- Provides a diet plan emphasizing foods rich in fiber, Vitamin C, and Zinc to promote healing.
- Suggests medications such as topical antibiotics (e.g., Mupirocin), oral antibiotics (only under doctor supervision), and dressing guidelines.
- Aims to help patients manage the condition better while seeking medical help.

6.7. Result Visualization Module

This module enhances user experience by:

- Displaying the uploaded image in base64 format on the web interface.
- Clearly showing whether an ulcer is detected or not.
- Listing the personalized diet and medication suggestions in a clean, readable format.

7. Results and Discussion

The Diabetic Foot Ulcer (DFU) Detection and Management system showed promising results in both ulcer detection and personalized recommendations. The system utilized a Convolutional Neural Network (CNN) model for DFU classification, which demonstrated an accuracy of 90%, indicating reliable detection of foot ulcers. The model achieved a sensitivity of 85% and specificity of 92%, suggesting that it effectively identifies ulcers while minimizing false positives. These results highlight the potential of the system in automating the detection of DFUs, especially in areas with limited access to healthcare.

The personalized recommendations provided by the system, including tailored diet plans and medical suggestions, received positive feedback from test users. Diet recommendations, aimed at controlling blood sugar levels and promoting wound healing, were appreciated for their practical application. Medical suggestions, such as foot care routines and guidance on when to seek medical attention, helped users feel more empowered in managing their condition. Users found the interface intuitive and easy to navigate, even with limited technical knowledge, making the system accessible to a wide range of diabetic patients.

However, some challenges were noted during the evaluation. Users requested more detailed medical guidance, such as pain management tips and wound care advice. Additionally, there was interest in integrating real-time monitoring and wearable device support to track healing progress and provide continuous feedback.

Future improvements will focus on enhancing the system's compatibility with various devices, optimizing the machine learning model to handle more complex cases, and incorporating real-time monitoring features. These enhancements aim to further improve the system's effectiveness and usability in managing diabetic foot ulcers.

Figure 3 User Interface for Ulcer Detected

Figure 4 User Interface for Non-Ulcer Detected

8. Conclusion

The CNN-Based Diagnostic System for Diabetic Foot Ulcer Analysis demonstrates significant potential in improving the early detection and management of diabetic foot ulcers. By leveraging advanced machine learning techniques, particularly Convolutional Neural Networks (CNNs), the system offers a reliable and accurate method for detecting foot ulcers, with an accuracy rate of 90%. This is a significant advancement over traditional manual methods, enabling early intervention that could reduce complications associated with DFUs.

Furthermore, the integration of personalized diet and medical care recommendations enhances the system's value. By providing tailored suggestions to control blood sugar levels, promote healing, and prevent further complications, the system empowers diabetic patients to manage their condition more effectively. The user-friendly interface ensures that even those with minimal technical expertise can easily navigate the platform, making it accessible to a wide range of users.

Despite its promising results, the system has room for improvement. Future developments should focus on enhancing the platform's compatibility with various devices, expanding the range of medical recommendations, and integrating real-time monitoring features. These enhancements could further improve the system's usability and provide a more comprehensive solution for managing diabetic foot ulcers.

Overall, the proposed system represents a significant step forward in the healthcare technology space, offering an innovative, accessible, and practical solution for diabetic foot ulcer detection and management, particularly for patients in remote or underserved areas.

Compliance with ethical standards

Disclosure of conflict of interest

There is no conflict of interest.

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Author's short biography

Mrs. A Sarala Devi

Mrs. A Sarala Devi is an Associate Professor with an M. Tech in Computer Science and Engineering and she holds a Ph.D. She has 13 years of professional experience in the field of computer science. Her research interests include Artificial Intelligence, Neural Networks.

G Soujanya I am G Soujanya, an undergraduate student pursuing a Bachelor's degree in Computer Science and Engineering with a specialization in Data Science. My research interest lies in Machine Learning, where I explore data-driven techniques and their applications. As an aspiring data science student, I am keen on expanding my knowledge and gaining hands-on experience in the field.	
S Sai Raj S Sai Raj is an undergraduate student pursuing a Bachelor’s degree in Computer Science and Engineering with a specialization in Data Science. His research interest lies in Artificial Intelligence, where she explores intelligent systems and their real-world applications. He is passionate about learning and applying AI techniques to solve complex problems.	
G Aniketh G Aniketh is an undergraduate student pursuing a Bachelor’s degree in Computer Science and Engineering with a specialization in Data Science. His research interest is in Data Science, where he explores data analysis techniques and their applications. He is eager to expand his understanding and contribute to advancements in the field.	
V Akhil V Akhil is an undergraduate student pursuing a Bachelor’s degree in Computer Science and Engineering with a specialization in Data Science. His research interest is in Data Science, focusing on extracting insights from data and developing data-driven solutions. He is keen on enhancing his knowledge and practical skills in this evolving field.