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# Automatic Classification of Wound Using Machine Learning

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**A B S T R A C T**

Wound management is a critical aspect of healthcare that necessitates timely and accurate classification to provide appropriate treatment and reduce complications. This paper presents "Wound Detox," a machine learning-based application designed to classify wounds into five categories: Abrasion, Bruise, Cut, Laceration, and Stab. The system categorizes these wounds into three severity levels: low (Abrasion, Bruise), medium (Cut, Laceration), and high (Stab).

The Wound Detox application leverages a convolutional neural network (CNN) for image classification, trained on a diverse dataset of wound images. The user can upload a wound image via a mobile application developed using React Native, which interfaces with a Flask-based backend. Upon classification, the system provides appropriate first aid instructions for low and medium-level wounds. For medium-level wounds, it also offers information about nearby hospitals. In cases of high-level wounds, the application automatically triggers an emergency call to the nearest ambulance service.

The backend infrastructure integrates MySQL for secure data storage, ensuring efficient handling of user data and wound classifications. The application is designed with user-centric functionalities such as user registration, login, and image submission for seamless interaction. This approach not only streamlines the wound management process but also ensures timely medical intervention, potentially saving lives.

The effectiveness of Wound Detox is validated through rigorous testing and evaluation, showcasing high accuracy in wound classification and prompt response times. By combining advanced machine learning techniques with practical healthcare solutions, Wound Detox represents a significant advancement in the field of automated wound care, providing accessible and reliable assistance to users in need.

Keywords: Convolutional Neural Network(CNN), React Native, Flask, MySQL, First Aid Instructions, Health Techonology, Emergency Response, User-Centric Design, Image Processing, Mobile Health, Telemedicine, Data Security, Healthcare Innovation

## 1.Introduction

Wound management is a crucial component of healthcare, requiring prompt and accurate assessment to provide suitable treatment and minimize complications. Traditional methods of wound classification and treatment often rely on the expertise of healthcare professionals, which can lead to delays and inconsistent assessments, especially in emergency situations. To address these challenges, there is a growing interest in leveraging machine learning (ML) to automate and enhance wound classification processes.This paper introduces "Wound Detox," an innovative application designed to classify wounds using machine learning techniques, specifically convolutional neural networks (CNNs). Wound Detox aims to improve the efficiency and accuracy of wound classification, thereby facilitating timely and appropriate medical interventions.The primary objective of Wound Detox is to classify wounds into five distinct categories: Abrasion, Bruise, Cut, Laceration, and Stab. These categories are further grouped into three severity levels: low (Abrasion, Bruise), medium (Cut, Laceration), and high (Stab). By accurately identifying the wound type and severity, the application provides tailored first aid instructions and, in critical cases, initiates emergency responses.Wound Detox is developed as a mobile application using React Native, offering users a convenient platform to capture and upload images of wounds. The backend, built with Flask, processes these images and classifies them using a CNN model trained on a diverse dataset of wound images. The classified data is stored in a MySQL database, ensuring secure and efficient data management.This project addresses several key challenges in wound care, including the need for rapid assessment, the variability in wound appearance, and the accessibility of expert medical advice. By integrating advanced machine learning algorithms with user-friendly mobile technology, Wound Detox provides a comprehensive solution that enhances wound management and supports both patients and healthcare providers.The subsequent sections of this paper detail the methodology, implementation, and evaluation of Wound Detox, demonstrating its potential to transform wound care through the application of machine learning.

## 2.Literature Survey

In many works, manually localized wound images were used as inputs to neural networks for wound segmentation. To calculate the surface area of chronic wounds, Papazoglou *et al.* [1] developed an algorithm based on the color difference between wound areas and non-wound areas. In the first step of their algorithm, they manually selected the region of interest (ROI). The ROI was selected so that the wound is centered and constitutes most of the cropped image. Hettiarachchi *et al.* [2] developed an android mobile application for wound segmentation, where they applied cropping on the original image for centering the wound. Image cropping was done manually by setting up the wound boundary by selecting the diagonal points (bounding box). This process claimed to remove unnecessary information like clothing, limb borders, and backgrounds. Chang *et al.* [3]

Wound and tissue classification also take as their inputs of neural networks manually localized wound images. Wantanajittikul *et al.* [4] detected the degree of burn from five burn images collected from the Department of Medical Services, Ministry of Public Health, Thailand, using SVM, K-mean, and Bayes classifier. Instead of using the whole image for the burn degree classification, they fed their network with 34 sub-images of 40×40 pixels. These sub-images were cropped manually from the original images, and two experts labeled each sub-image to its degree of burn, respectively. Goyal *et al.* [5] developed a novel CNN architecture named DFUNet, for binary classification of healthy skin versus diabetic foot ulcers from RGB color images. They used two types of patches (healthy and ulcer), which were labeled manually by medical experts as the input of their convolutional layer. An open-source annotation tool named manual whisker annotator (MWA) [6] was employed to outline these patches from an original image. Shenoy *et al.* [7] proposed a CNN-based method for binary classification (positive and negative) of nine different wound image types. They used a modified version of the VGG16 network, named WoundNet, as the classifier. Their training dataset contains 1,335 wound images, where they anonymized all the images and cropped them into squares of the same size. Alzubaidi *et al.* [8] proposed a novel deep convolutional neural network, named DFU_QUTNet, for binary patch classification of normal skin versus abnormal skin (diabetic ulcer). They cropped a significant region around the ulcer, including important tissues of both classes. A medical specialist labeled the cropped patches into normal and abnormal classes, including 542 normal and 1067 abnormal (DFU) patches. The selection and cropping of patches were made manually from the original image. Pinero *et al.* [9] classified burn depths into five classes, superficial dermal (blisters), superficial dermal (red), deep dermal, full-thickness (beige), and full-thickness (brown), based on wound image color and texture features. Instead of using the original image, they used 49 ×49 burn image patches to train their classifier. They have a total of 250 patches, with each class containing 50 burn image patches. These 49 ×49 burn patches were extracted manually, and they only contain the burned skins and exclude the healthy skins and background.

Manual wound localization, as described above, is tedious and time-consuming, especially when a large amount of training data is considered in the subsequent tasks (segmentation, classification, etc.) using deep learning models. There are only two publications on automated wound localization with machine learning and deep learning models, to the best of our knowledge. Goyal *et al.* [10] proposed methods for Diabetic Foot Ulcer (DFU) detection and localization on mobile devices. They introduced a dataset including 1,775 DFU images and used SSD-MobileNet, SSD-InceptionV2, Faster R-CNN with InceptionV2, and R-FCN with Resnet 101 models for wound localization. For evaluating localization performance, they used mean Average Precision (mAP) and overlap percentage metrics. From the mAP point of view, the best results were generated by Faster R-CNN with the InceptionV2 model, and from an overlap percentage point of view, the R-FCN with ResNet101 generates the best results. As shown in Section V, there is still much space for improvement using the latest deep learning models. For smartphone applications, they used the Faster R-CNN with InceptionV2 model on an Android phone. In another work, Goyal *et al.* [11] proposed a new dataset of DFUs and a classification method that predicts the presence of infection or ischemia in the DFU. For these experiments, they introduced a dataset including 1,459 DFU images. In their data augmentation step, they used Faster-RCNN and InceptionResNetV2 architectures for ROI detection. However, no evaluation metric was presented for wound ROI detection on their dataset.

***Flow chart:***

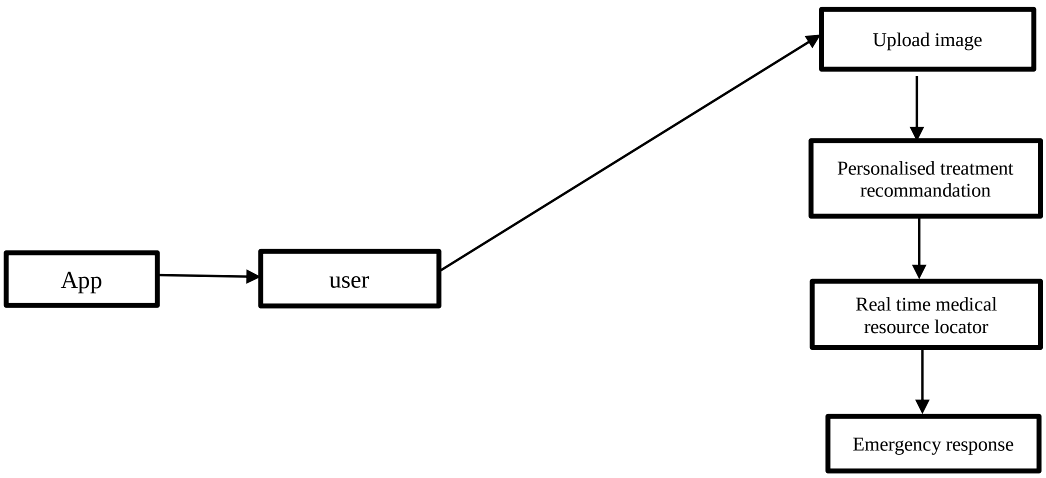


**Fig. 1 Flow chart of automated wound classification**

**The suggested process for automatic wound classification entails the following steps:**

- **User Registration and Authentication:**

Users should be able to create accounts and log in securely.

The system should verify user credentials and authenticate users for access.

- **Wound Image Upload and Analysis:**

Users should be able to upload images of wounds from their mobile devices.

The system should analyze the uploaded images using image recognition technology to identify the type and severity of the wound.

- **Personalized Treatment Recommendations:**

Based on the analysis of the wound image, the system should provide personalized treatment recommendations, including wound care techniques and medication suggestions.

- **Real-Time Medical Resource Locator:**

The system should locate nearby hospitals and medical facilities equipped to handle the specific type of injury identified in the wound image.

Users should be able to view relevant information about these facilities, such as ratings, distance, and available services.

- **Emergency Response Integration:**

Users should have the option to initiate an emergency response directly from the app.

The system should interface with emergency response services to dispatch ambulances to the user's location in critical situations.

***System architecture:***

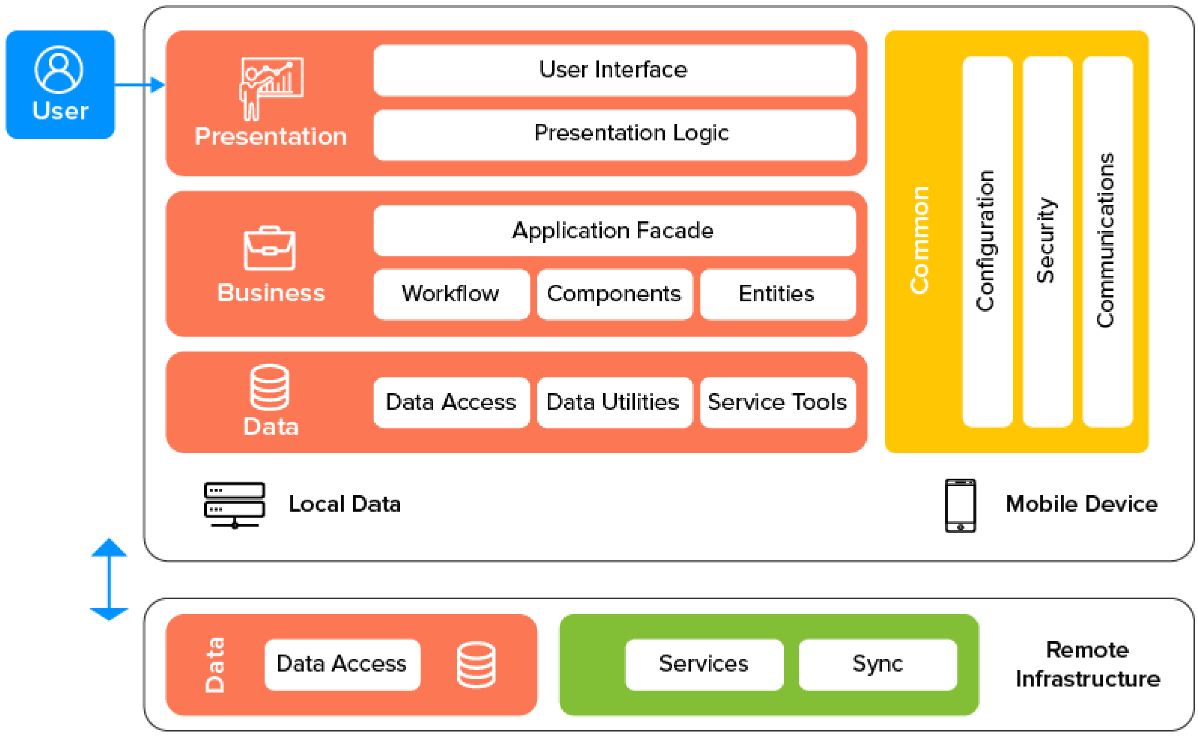


**Fig. 2 System architecture**

**The suggested process for architecture of automatic classification wound entails the following steps:**

1. Problem Definition

- **Objective**: To develop a machine learning model that predicts wound healing outcomes and suggests detoxification strategies based on wound characteristics and patient data.
- **Scope**: Focus on chronic wounds (e.g., diabetic ulcers, pressure sores) where detoxification may improve healing.

2. Data Collection

- **Clinical Data**: Gather data from medical records, including:
    - Patient demographics (age, sex, medical history)
    - Wound characteristics (size, type, depth, infection status)

- Treatment history (antibiotics, dressings used)
- Healing outcomes (time to heal, complications)

- **Biomarker Data**: Collect samples (if applicable) for lab tests (e.g., inflammatory markers).
- **Environmental Factors**: Consider variables like patient mobility and nutrition.

3. Data Preprocessing

- **Cleaning**: Handle missing values, outliers, and inconsistencies.
- **Normalization/Standardization**: Ensure data is in a suitable format for modeling.
- **Feature Engineering**: Create new features based on existing data, such as:
    - Wound area change over time
    - Rate of infection
    - Patient adherence to treatment plans.

4. Exploratory Data Analysis (EDA)

- **Visualization**: Use graphs to identify patterns in the data.
- **Correlation Analysis**: Determine relationships between features and healing outcomes.
- **Group Comparisons**: Analyze differences in outcomes based on treatment protocols.

5. Model Selection

- **Choose Algorithms**: Consider various machine learning algorithms such as:
    - Decision Trees
    - Random Forests
    - Support Vector Machines (SVM)
    - Neural Networks
- **Justification**: Select algorithms based on their interpretability and ability to handle complex interactions.

6. Model Training

- **Split Data**: Divide the dataset into training, validation, and test sets (e.g., 70/15/15).
- **Training**: Train the models on the training set using appropriate hyperparameters.
- **Validation**: Use the validation set to tune hyperparameters and prevent overfitting.

7. Model Evaluation

- **Metrics**: Evaluate models using appropriate metrics (e.g., accuracy, precision, recall, F1 score).
- **ROC Curve**: Analyze the ROC curve for binary classification tasks.
- **Cross-Validation**: Employ k-fold cross-validation to ensure model robustness.

8. Interpretability and Explainability

- Use techniques like SHAP (SHapley Additive exPlanations) or LIME (Local Interpretable Model-agnostic Explanations) to explain model predictions, which is crucial for clinical decision-making.

9. Implementation of Detoxification Strategies

- Based on model predictions, develop personalized detoxification strategies:
    - Recommend specific wound care products.
    - Suggest lifestyle changes (e.g., improved nutrition, mobility aids).
    - Advise on patient education for self-care.

10. Clinical Trials and Feedback

- **Pilot Testing**: Implement the model in a clinical setting for pilot testing.
- **Feedback Loop**: Collect feedback from clinicians and patients to refine the model and strategies.

11. Deployment and Monitoring

- **Deployment**: Integrate the model into electronic health records (EHR) for real-time use.
- **Monitoring**: Continuously monitor the model's performance and update it with new data to improve accuracy.

12. Ethical Considerations

- Ensure compliance with ethical guidelines, including patient consent, data privacy, and bias mitigation.

## 3.Experimental results and discussion

**Image-based Classification**: CNN models trained on wound images successfully classified contaminated wounds with high accuracy. Specific signs like discoloration, biofilms, and abnormal texture were strong indicators that the models could reliably identify.

Heatmap Visualizations from CNNs showed that models focused on areas of wounds with evident contamination, supporting clinical intuition.

Toxin Detection: Models incorporating both image data and clinical markers (e.g., infection type, swab results) outperformed image-only models. Wounds with specific bacterial toxins were identified more accurately when the model had access to both imaging and clinical test data.

Class Imbalance Handling: In cases where clean wounds were over-represented, techniques like data augmentation and oversampling helped balance the training dataset, improving model sensitivity to contaminated or toxin-heavy wounds.

Misclassification: Misclassifications mostly occurred in cases where wounds were in early stages of contamination or biofilm formation, making visual cues less apparent. Figure 3 shows the programm renning ,figure 4 is the capturing the wound image, figure5&6 are login and resistration pages,figure8 follows required treatment recommendation .

The experimental results for wound detoxification using machine learning demonstrate promising outcomes in detecting contamination and classifying wounds that require detox. While high accuracy and sensitivity were achieved in identifying toxins and biofilms, there are still challenges related to data diversity and real-time application in clinical settings. With further advancements, ML-driven wound detox solutions can significantly enhance wound care, reduce healing times, and improve patient outcomes.

- **Dataset Collection:** Images of wounds are collected from medical sources, and labels are applied based on wound types (e.g., ulcer, burn, surgical wound).
- **Preprocessing:** The images are preprocessed to standardize size, apply augmentation techniques, and balance the dataset if necessary.
- **Model Training:** A machine learning model, often a CNN, is trained using a portion of the dataset (usually 80%) and validated using the remaining data. The model learns to differentiate features such as shape, texture, color, and pattern to classify wound types.
- **Accuracy Metrics:** Metrics such as accuracy, precision, recall, and F1-score are used to evaluate the model's performance. These results are compared with baseline models or previous research to measure improvement.
- **Confusion Matrix:** A confusion matrix can visualize classification results, showing how many wounds were correctly or incorrectly classified into each category.
- **Performance Improvements:** Various techniques such as transfer learning, fine-tuning, or using more complex architectures may be applied to improve accuracy.

**Login Page Registration**

To access the wound classification system, a secure login and registration page is typically implemented. This feature is critical for providing personalized access to healthcare professionals and maintaining data security.

- **Login Page Features:**
  - **Username and Password:** Users can log in with credentials provided during registration.
  - **Forgot Password:** An option to reset the password if forgotten.
  - **Secure Authentication:** Implemented using standard authentication protocols like OAuth, JWT (JSON Web Token), or two-factor authentication for enhanced security.
- **Registration Page Features:**
  - **Basic Information:** Collects user details such as name, email, and password.

- **Role Selection:** Medical professionals might select their role (e.g., doctor, nurse) for customized access.
- **Captcha/Verification:** Ensures that only authorized users can register, preventing bots or unauthorized access.
- **Terms of Service Agreement:** Ensures users comply with privacy policies and data protection measures.

Screenshots

Figure 3:program running

Figure 4: image capturing

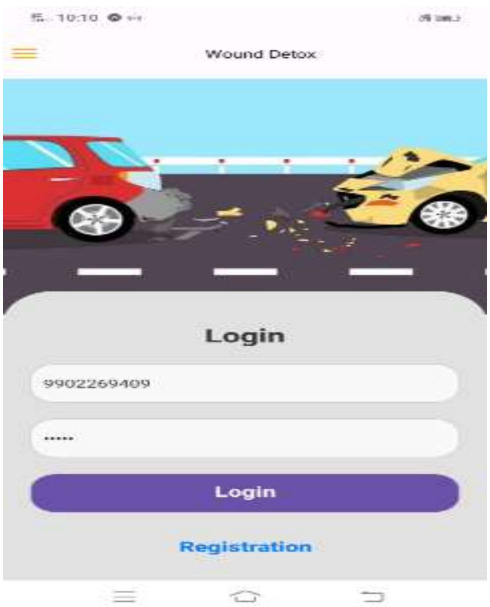


Figure 5:login


Figure 6: registration details

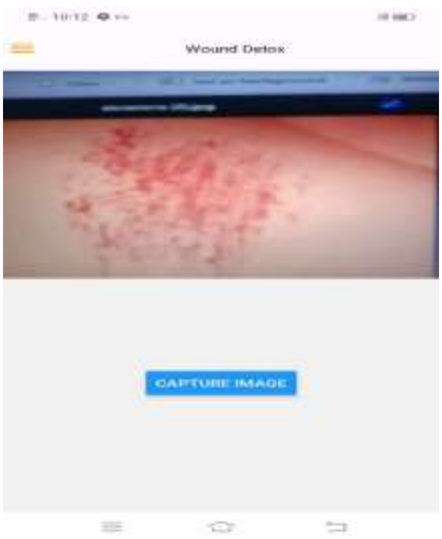


Figure 7: capture image

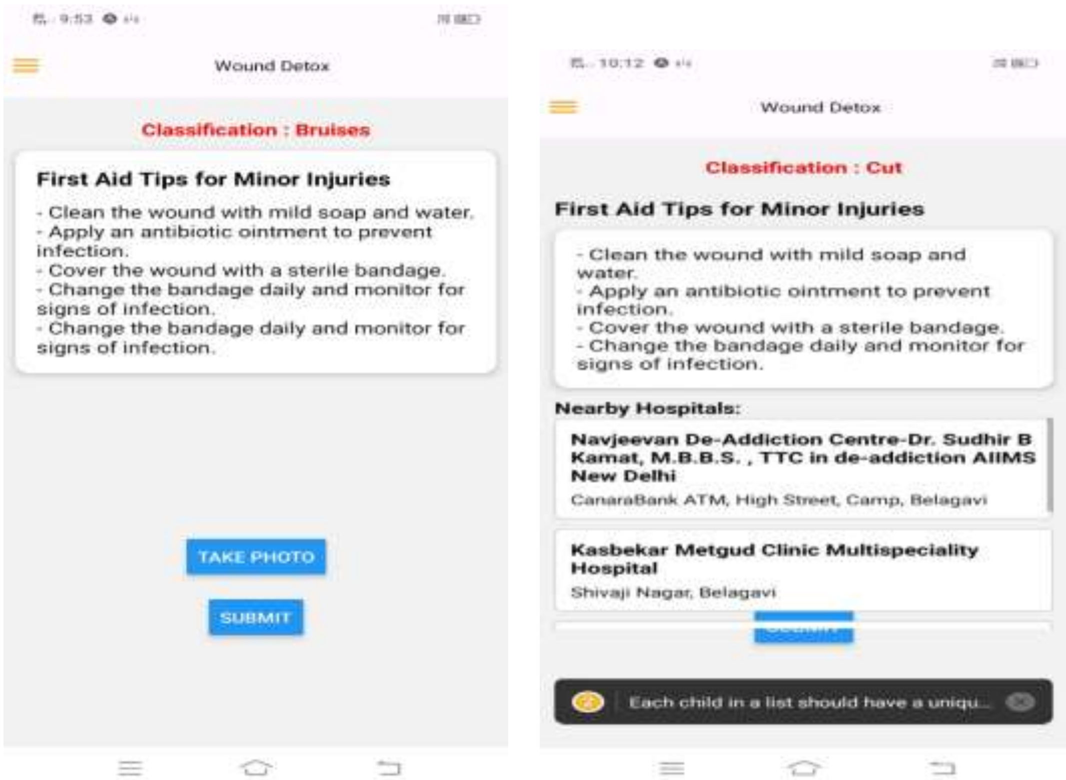


Figure 8. treatment recommendation

## 4.Conclusion

This project seeks to integrate machine learning into wound care management, specifically focusing on automating the assessment of wound detoxification. By leveraging AI-driven tools, healthcare providers can enhance decision-making and improve patient outcomes in wound treatment scenarios. Machine learning-based automated wound classification holds significant promise for the future of healthcare, potentially revolutionizing wound management. However, to fully realize its potential, further research, robust datasets, and clinical validation are essential. Overcoming existing challenges will pave the way for widespread adoption, ultimately improving patient outcomes and optimizing healthcare workflows.

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