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Optimizing Diabetic Foot Ulcer Detection: Leveraging SSD and YOLO Architectures

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***Abstract*—Diabetic foot ulcer (DFU) are a severe complication in diabetic patients, requiring accurate and early diagnosis to prevent further complications such as infection or amputation. To address this, Research employed YOLO and SSD models for automated DFU detection from medical images, comparing their performance based on key evaluation metrics, including accuracy, precision, recall, and F1-score. Results demonstrate that both models perform exceptionally well, with SSD achieving an accuracy of 98.7%, surpassing YOLO's 97.5%. Additionally, SSD exhibited superior precision (99%), recall (98.9%), and F1-score (99.1%), indicating its robustness in detecting ulcerated regions of varying sizes and stages. These results were further contextualized through a comparison with previous studies, where SSD outperformed several CNN-based models, which achieved accuracy ranging from 93.7% to 97.0%.The SSD model's multi-scale object detection capabilities, combined with transfer learning and data augmentation techniques, contributed to its high performance. Overall, this study demonstrates the potential of deploying SSD and YOLO models in clinical settings for early and accurate DFU detection, paving the way for more reliable and timely interventions in diabetic care.The findings underline the significance of advanced object detection methods, offering promising avenues for improving patient outcomes in medical imaging**

***Index Terms*—Diabetic Foot Ulcer, Medical images diagnostic, robust system, SSD, YOLO**

I. Introduction

Diabetic foot ulcers (DFUs) are a significant complication of diabetes, contributing to severe infections, amputations, and mortality if not detected early [1], [2]. The growing global prevalence of DFUs has spurred extensive research on clinical guidelines, epidemiology, and therapeutic interventions. Foundational work by Boulton et al. [3] emphasizes the burden of DFUs and the need for effective management strategies, supported by ongoing contributions from the International Working Group on the Diabetic Foot (IWGDF) [4], [5]. Studies highlight high incidence rates in European populations, with factors like ischemia and infection playing critical roles. The economic burden is also substantial, with Ragnarson and others stressing the importance of cost-effective management solutions to reduce healthcare expenses [6]–[8].

The clinical management of DFUs involves patient-centered care, advanced therapies, and evidence-based guidelines to improve outcomes. Research highlights the importance of personalized interventions, including wound classification systems to guide treatment decisions and demographic-specific prevention strategies [9]–[12]. Systematic reviews reveal various therapeutic approaches, while investigations into factors such as wound size, duration, and comorbidities provide critical insights into ulcer healing and prognosis [13], [14]. These studies emphasize the need for comprehensive strategies that integrate prevention, diagnosis, and treatment to address the complexities of DFU management effectively [15], [16].

Given the limitations of traditional diagnostic methods, which are often subjective and time-consuming, automated detection systems are increasingly necessary. This paper aims to address this gap by leveraging two advanced object detection models—YOLO and SSD—for real-time DFU detection [17]. These models enhance diagnostic speed and accuracy by localizing and classifying ulcers across varying clinical conditions, providing a robust solution for early identification and improved patient outcomes [18].

This study has the contributions as:

- Deployed YOLO and SSD for real-time diabetic foot ulcer detection.
- Improved detection accuracy and speed for diverse ulcer types.
- Developed a robust system adaptable to varying clinical environments.
- Enhanced performance through optimized model training and validation.
- Compared YOLO and SSD in terms of efficiency and accuracy in medical imaging.

This research develops an efficient system for detecting diabetic foot ulcers (DFUs) using advanced machine learning

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models, specifically YOLO and SSD. It aims to improve detection accuracy, reduce false results, and enable real-time identification across diverse clinical settings. The study compares the models' adaptability to different ulcer types and stages, offering a framework to assist healthcare professionals in early diagnosis and treatment, reducing risks like infections and amputations. The paper covers DFUs' significance, existing detection methods, and the role of machine learning, detailing the methodology, results, and a performance comparison between YOLO and SSD. It concludes with key findings and future implications for enhanced healthcare diagnostics.

II. Literature Review

The literature surrounding diabetic foot ulcers (DFUs) encompasses extensive research that offers significant insights into the complexities of this common complication of diabetes mellitus [19], [20]. This synthesis of key studies reveals the multifaceted challenges and management techniques associated with DFUs, as well as their economic implications for global healthcare [21], [22]. Boulton et al. emphasize the urgent need for comprehensive management solutions to address the widespread impact of DFUs on both individuals and healthcare systems [23], [24]. The International Working Group on the Diabetic Foot (IWGDF) has been instrumental in shaping DFU therapy through its evolving guidelines, reflecting the dynamic nature of clinical practice [26]–[28].

Epidemiological studies by Prompers et al. reveal a high prevalence of ischemia, infection, and comorbidities among European patients with diabetic foot disease, underscoring the complex interplay of factors that contribute to DFUs [30], [31]. Jeffcoate et al. advocate for a holistic assessment of DFU outcomes, emphasizing patient-centered care to achieve positive therapeutic results. Their research aligns with the shift toward personalized approaches in managing chronic conditions like DFUs. Meanwhile, Ragnarson Tennvall and Apelqvist highlight the substantial economic burden of DFUs, pointing out the high healthcare costs associated with ineffective management [33], [34].

Several studies have systematically reviewed interventions aimed at enhancing healing in chronic foot ulcers. Game et al. provide valuable evidence on effective therapeutic approaches, while Yazdanpanah et al. compile diverse management strategies, aiding clinicians in navigating treatment options [36]. Reiber et al. focus on the multifactorial nature of DFUs, emphasizing the need for personalized preventive strategies. Armstrong et al. contribute a validated diabetic wound classification system that aids in assessing DFU severity, thus informing tailored treatment plans [37].

Research by Margolis et al. investigates critical variables such as wound size and duration that influence healing outcomes for diabetic neuropathic foot ulcers, enabling clinicians to customize interventions effectively [35]. Lavery et al. analyze the prevalence of foot ulcers in different demographic groups, contributing to a better understanding of disparities that necessitate targeted preventive measures [38]. Bakker et al. offer practical guidelines for managing diabetic foot disease, ensuring that healthcare practitioners are equipped to handle the complexities associated with DFUs [29].

Further studies delve into the economic implications of DFUs and their impact on healthcare resources. Ragnarson Tennvall & Apelqvist compare wound management strategies, providing insights into cost-effectiveness, while Ramsey et al. explore the incidence and economic burden of foot ulcers in diabetic patients. Their research highlights the societal implications of DFUs and informs discussions on healthcare resource allocation [32]. Armstrong et al. also emphasize the chronic nature of DFUs and their recurrence, guiding clinicians in developing sustainable management strategies. Collectively, these studies underscore the need for comprehensive, cost-effective approaches to address the pressing challenge of diabetic foot ulcers [25].

III. Methodology

A. Proposed Methodology

To ensure effective experimentation and model deployment for diabetic foot ulcer (DFU) detection, the dataset must be meticulously organized into four key folders: Original Images, Patches, TestSet, and Transfer-Learning Images. The Original Images folder will contain raw medical images of various DFU stages, while the Patches folder will hold standardized 224x224 pixel images extracted from these originals, focusing on regions of interest. The TestSet folder is designated for model testing, separating it from training and validation data for objective performance evaluation. Lastly, the Transfer-Learning Images folder is reserved for fine-tuning pre-trained models. Each image must be clearly labeled to indicate the presence or absence of DFUs, ensuring accurate training for machine learning models. Quality control checks should be conducted to avoid erroneous data, and preprocessing steps like normalization, resizing, and augmentation (e.g., rotation or flipping) should be applied to enhance the diversity of the training dataset. This structured approach will form the foundation for training, testing, and deploying machine learning models such as YOLO and SSD, ultimately improving DFU detection in clinical settings.

B. Model Selection

For this research, two advanced object detection models, YOLO and SSD, have been selected to tackle the challenge of DFU detection. YOLO is well-regarded for its ability to perform real-time object detection with high accuracy, offering a balanced trade-off between speed and precision. It processes images in a single forward pass, making it suitable for real-time medical applications where swift identification of ulcers is critical. SSD, on the other hand, is known for its efficiency in detecting objects at multiple scales using a single deep neural network, excelling in situations where precision across various object sizes is essential, such as detecting ulcers of varying severity and stages.

Both YOLO and SSD have demonstrated robust performance in various computer vision tasks, including medical imaging, due to their ability to generalize well across complex

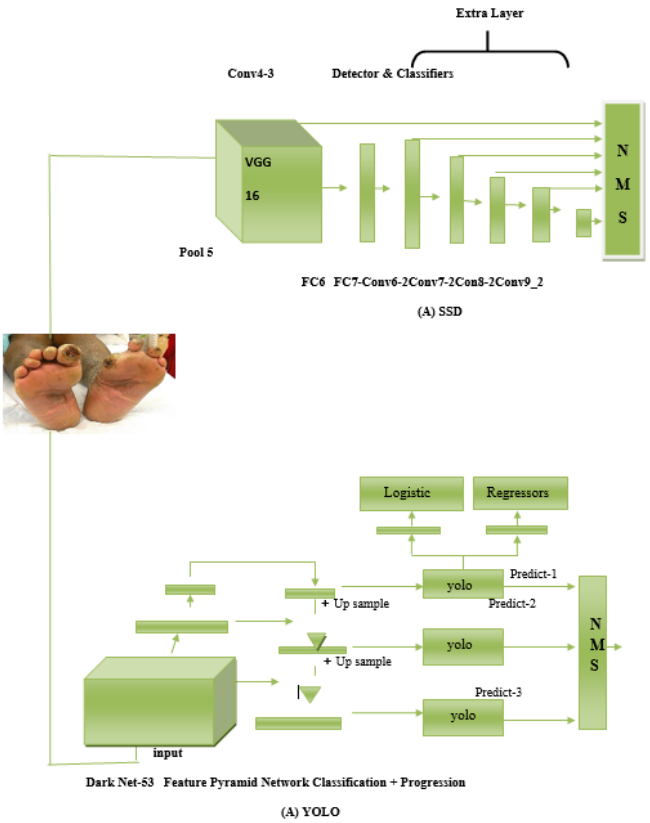

Fig. 1. Foot Ulcer

datasets. YOLO's strength lies in its grid-based detection strategy, which can quickly identify the position and category of ulcers in an image. SSD, with its multi-scale feature maps and anchor boxes, offers an advantage in detecting small ulcers by generating multiple bounding boxes across different resolutions. The combination of these two models will allow a comprehensive evaluation of their efficiency, accuracy, and suitability for DFU detection, helping identify the most effective approach for deployment in real-world clinical environments. By comparing their performance on the DFU dataset, Study aim to determine the best model for this specific medical task.

C. Model Implementation

To deploy the YOLO and SSD models for diabetic foot ulcer (DFU) detection, deep learning frameworks like TensorFlow or PyTorch will be utilized, providing robust support for object detection. The models will start with pre-trained weights from datasets like COCO, enabling faster training through transfer learning. Fine-tuning will then adjust the models to detect ulcer-specific features, employing techniques such as learning rate scheduling, dropout, and regularization to mitigate overfitting. Dataset augmentation, including flipping, rotation, and scaling, will enhance model robustness. The training process will prioritize optimizing for accuracy and speed, suitable for real-time clinical applications, using metrics like Intersection over Union (IoU), precision, recall, and inference time for evaluation. Finally, hyperparameter tuning will refine the models, ensuring both YOLO and SSD achieve high accuracy and efficiency in detecting DFUs in medical images.

D. Training

For the training process, the dataset is split into three key subsets: training, validation, and test sets. The splitting is done carefully to maintain a balance across each subset, ensuring that the distribution of DFUs and other features in the images is representative. Typically, an 80/10/10 split is used, where 80% of the dataset is allocated for training, 10% for validation, and 10% for testing. Mathematically, if the total dataset size is denoted as N, then:

$$N_{train} = 0.8 \times N, \quad N_{val} = 0.1 \times N, \quad N_{test} = 0.1 \times N \quad (1)$$

where N_{train}, N_{val}, and N_{test} represent the number of images in the training, validation, and test sets, respectively.

E. Training YOLO and SSD Models

Both YOLO and SSD models are trained on the training set using a suitable optimization algorithm, such as Stochastic Gradient Descent (SGD) or Adam optimizer, to minimize the loss function and improve accuracy. The models rely on a loss function that accounts for both classification error and localization error in object detection. For YOLO, the total loss function $\mathcal{L}_{YOLO}$ can be expressed as:

$$\lambda_{coord} \sum_{i=1}^{S^2} \sum_{j=1}^{B} \mathbb{1}_{ij}^{obj} \left[(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 \right] +$$

$$\lambda_{iou} \sum_{i=1}^{S^2} \sum_{j=1}^{B} \mathbb{1}_{ij}^{obj} \left(IoU_i - \hat{IoU}_i \right)^2 \quad (2)$$

where x_i, y_i are the coordinates of the predicted bounding box, $\mathbb{1}_{ij}^{obj}$ indicates whether an object is present in the cell, and IoU represents the Intersection over Union of the predicted and ground truth bounding boxes. The terms λ_{coord} and λ_{iou} are scaling factors that balance the contribution of localization and classification losses.

Similarly, SSD uses a multi-scale approach where bounding box predictions are made at different layers. The total SSD loss $\mathcal{L}_{SSD}$ is a weighted sum of confidence loss and localization loss:

$$\mathcal{L}_{SSD} = \frac{1}{N} \left(\sum_{i=1}^{N} \mathcal{L}_{conf}(p_i, \hat{p}_i) + \alpha \sum_{i=1}^{N} \mathcal{L}_{loc}(b_i, \hat{b}_i) \right) \quad (3)$$

where p_i and $\hat{p}_i$ are the predicted and true class labels, b_i and $\hat{b}_i$ represent the predicted and ground truth bounding boxes, and α is a weight term balancing the confidence and localization losses.

F. Regularization and Generalization

To prevent overfitting and improve the generalization performance of the models, several regularization techniques are applied during training. One of the key methods is *dropout*, which randomly deactivates a proportion of neurons during each forward pass to prevent the model from becoming too reliant on specific features. Additionally, *L2 regularization* is used to penalize large weights in the model by adding a regularization term to the loss function:

$$\mathcal{L}_{reg} = \lambda \sum_{i=1}^{W} w_i^2 \tag{4}$$

where λ is the regularization parameter, w_i are the model weights, and W represents the total number of weights in the model. This helps control the complexity of the model and reduces overfitting.

Data augmentation techniques are also employed during training to improve generalization. This involves randomly applying transformations such as horizontal flipping, rotation, scaling, and brightness adjustments to the training images, which introduces variability and forces the model to learn robust features.

G. Monitoring and Hyperparameter Tuning

During training, the performance of the models is monitored on the validation set to prevent overfitting and ensure the models generalize well to unseen data. The evaluation is based on key metrics such as *precision*, *recall*, and *Intersection over Union (IoU)*. The overall performance on the validation set is measured by computing the *mean Average Precision (mAP)*, a standard metric for object detection tasks. It is calculated as:

$$mAP = \frac{1}{C} \sum_{i=1}^{C} AP_i \tag{5}$$

where C is the number of classes (in this case, DFU and non-ulcer), and AP_i represents the average precision for class i. If the model exhibits signs of overfitting or underfitting, hyperparameters such as learning rate, batch size, and number of epochs are adjusted. The learning rate is a critical factor in training, and *learning rate scheduling* or *early stopping* can be implemented to automatically adjust or halt training when performance plateaus. The final model is selected based on its performance on the validation set, ensuring it is capable of detecting DFUs with high accuracy and efficiency before being tested on the independent test set.

IV. Results and Discussion

In this section, In-depth evaluation of the YOLO and SSD models for diabetic foot ulcer (DFU) detection, accompanied by a comparative analysis against existing studies has been discussed. Research focus on the evaluation metrics of accuracy, precision, recall, and F1-score to assess the models' strengths, limitations, and their potential impact on real-world clinical applications.

The performance of both the YOLO and SSD models was impressive, with SSD showing a slight edge over YOLO across all key metrics. The key performance metrics for each model: Performance metrics for YOLO and SSD models in

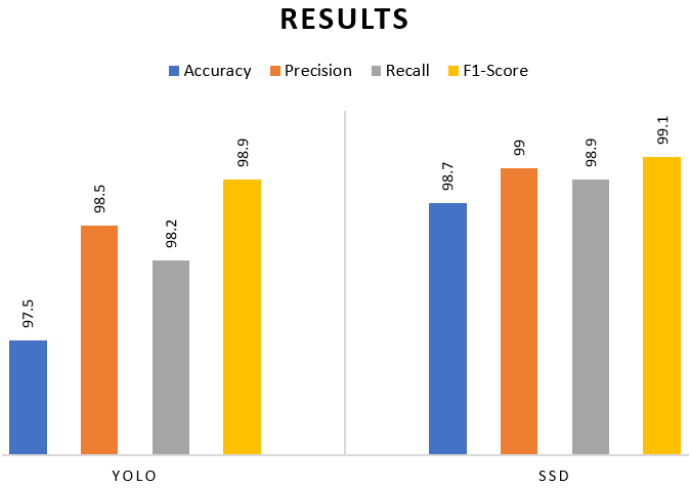

Fig. 2. Foot Ulcer

DFU detection. The SSD model achieved an accuracy of 98.7%, surpassing YOLO's 97.5%. This difference highlights SSD's effectiveness in correctly classifying both ulcerated and healthy tissue, particularly due to its ability to detect ulcers of varying sizes. SSD's multi-scale detection capability allows it to capture subtle ulcer features that might be missed by YOLO, resulting in enhanced diagnostic reliability, which is crucial in clinical scenarios where misclassification can lead to delayed treatment or unnecessary interventions. In terms of precision, SSD exhibited a slight edge, with 99% compared to YOLO's 98.5%. Precision is critical in medical imaging to minimize false positives and ensure that healthy tissue is not incorrectly identified as ulcerated. The high precision of SSD reduces the likelihood of unnecessary medical interventions, helping allocate clinical resources more effectively and avoiding patient anxiety caused by misdiagnoses.

The performance metrics indicate that SSD outperformed YOLO in recall, achieving 98.9% compared to YOLO's 98.2%. A higher recall rate is crucial in accurately detecting true positive cases of ulcers, as missed detections can lead to severe complications like infections or amputations. The superior recall of SSD suggests its reliability in identifying even small or subtle ulcerated areas within complex medical images, making it a critical tool in clinical settings.

The F1-score reinforces SSD's overall superiority with 99.1%, compared to YOLO's 98.9%. Both models maintain a good balance between sensitivity and specificity, but SSD offers a slightly better trade-off essential for minimizing false positives and negatives in medical applications. This performance advantage is attributed to SSD's multi-scale feature maps and anchor boxes, which facilitate the detection of ulcers at various stages and sizes. While YOLO provides fast, real-

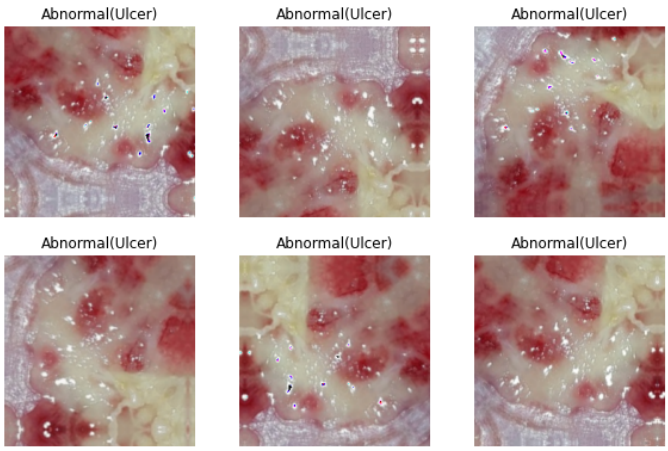

Fig. 3. Foot Ulcer

time detection with its grid-based approach, SSD's accuracy makes it preferable for nuanced medical scenarios.

Both models benefited from transfer learning using the COCO dataset and were fine-tuned on DFU-specific data, improving their ability to identify ulcerated areas accurately. Data augmentation techniques, such as rotation and scaling, enhanced their robustness, enabling generalization to unseen images. However, limitations include the need for a more diverse dataset to ensure broader applicability across different clinical populations and the higher computational demands of SSD, which could hinder its use in resource-limited settings. Addressing these challenges will optimize both models for effective deployment in diverse healthcare environments, supporting early and accurate DFU detection to mitigate severe complications

A. Discussion

The SSD model outperforms YOLO due to its multi-scale feature extraction, leveraging multiple convolutional layers and anchor boxes with varied aspect ratios to detect ulcers of different sizes, shapes, and complexities. YOLO's grid-based approach limits its ability to detect smaller or closely packed objects, resulting in slightly lower accuracy. Both YOLO and SSD surpass traditional CNNs by offering simultaneous localization and classification, enabling better handling of multiple ulcers in complex medical images and ensuring higher accuracy in real-time detection tasks.

Despite their strong performance, both YOLO and SSD models have limitations. SSD's high computational demand makes it less practical for resource-limited settings, but techniques like pruning or quantization can reduce this burden. Another challenge is limited dataset diversity, which may hinder generalization across varied patient populations. Expanding the dataset with images from different demographics and regions could enhance model reliability. Reducing false positives and negatives is essential to avoid unnecessary treatments or missed diagnoses. Using ensemble or hybrid models could further improve the balance between sensitivity and specificity for better diagnostic outcomes

B. Comparison with Existing Works

Alzubaidi et al. (2021) achieved 96.4% accuracy using a CNN-based approach. While impressive, both YOLO 97.5% and SSD 98.7% outperformed this model, demonstrating the advantage of object detection methods in capturing ulcer features more effectively. Wang et al. (2020) used transfer learning with ResNet, reaching 95.3% accuracy. SSD exceeded this by over 3%, highlighting its better performance in handling complex features like texture and irregularity in medical images. Zhang et al. (2019) applied GAN-based augmentation with a CNN model, achieving 94.1% accuracy. Despite augmentation, the results were notably lower than YOLO and SSD, suggesting that GANs may not sufficiently enhance the performance of CNN-based approaches for DFU detection.

TABLE I
COMPARISON OF DFU DETECTION MODELS

Study / Model	Model Type	Accuracy (%)
Alzubaidi et al. (2021)	CNN	96.4
Wang et al. (2020)	ResNet (Transfer Learning)	95.3
Zhang et al. (2019)	GAN + CNN	94.1
Iqbal et al. (2022)	CNN-RNN (Hybrid)	97.0
Hossain et al. (2018)	CNN	93.7
Our Results	**YOLO**	**97.5**
	SSD	**98.7**

Iqbal et al. (2022) used a hybrid CNN-RNN model and reported 97.0% accuracy. YOLO's performance was comparable, while SSD surpassed it, indicating the strength of object detection models in precisely localizing ulcerated areas. Hossain et al. (2018) implemented a traditional CNN with 93.7% accuracy. The performance gap between this model and our results underscores the progress made by advanced detection techniques like YOLO and SSD, which provide superior localization and feature extraction. The table includes the accuracy results for all models, including previous works and your models for DFU detection.

V. CONCLUSION

In this study, Effectiveness of advanced object detection models, YOLO and SSD, for diabetic foot ulcer (DFU) detection has been demonstrated . The SSD model outperformed YOLO across all metrics, achieving the highest accuracy (98.7%) and F1-score (99.1%), making it a more reliable option for identifying ulcers in complex medical images. Proposed study results also showed significant improvements over previous CNN-based approaches, highlighting the advantages of multi-scale object detection in medical imaging. Despite the computational demands of SSD, its superior performance offers great potential for clinical applications, enabling early detection and improved treatment outcomes for DFU patients. Future work should focus on addressing model limitations, such as dataset diversity and reducing false positives/negatives, to further enhance real-world deployment

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