A Framework for Advancing Burn Assessment With Artificial Intelligence

Md Masudur Rahman, PhD[1]; Mohamed El Masry, MD, PhD[2,3]; Surya C. Gnyawali, PhD[2,3]; Yexiang Xue, PhD[4]; Gayle Gordillo, MD[2,5]; Juan P. Wachs, PhD[1]

ABSTRACT

Introduction:

Burn injuries are a significant challenge in clinical and military settings, requiring accurate and timely assessment to guide treatment. Traditional methods for determining burn depth, a key factor in severity, rely heavily on subjective evaluation, leading to variability and delays in decision-making. Advances in Artificial Intelligence (AI) offer solutions to improve diagnostic accuracy and standardization. This study aims to evaluate the diagnostic performance of an AI model for burn depth assessment by comparing its outputs against a gold standard—focusing on image-based diagnosis of burn type and depth.

Materials and Methods:

This study analyzed 29 burn patients, under an Institutional Review Board-approved protocol (IRB# 12,689) at the Eskenazi Burn Center, Indianapolis. Digital images of burns were collected and classified into 3 burn depth categories: first-degree, second-degree, and third-degree. The AI model was fine-tuned on 131 annotated digital images, augmented to 1,200 using techniques such as rotation, flipping, and brightness adjustment. Style transfer using a machine learning models (called GAN) was used to further enhance the dataset by simulating burn variations. Zero-shot (meaning no previous training) segmentation, employing pretrained foundation models, was used to localize burn regions without task-specific training.

Results:

The proposed AI prediction model achieved 79% accuracy in classifying 3 burn depth categories. Data augmentation improved performance, while segmentation demonstrated strong utility, particularly in identifying burn regions effectively in diverse scenarios. Style transfer augmented the dataset by simulating realistic burn appearances, further enhancing model robustness. Zero-shot segmentation, meaning it identified burn areas without any prior training on similar images, successfully localized burn regions, aligning with clinical expectations.

Conclusions:

This study highlights the potential of AI in improving burn depth classification and segmentation. The results demonstrate that integrating AI-driven models into clinical care can enhance diagnostic accuracy, efficiency, and scalability, offering transformative tools for clinical and military applications in burn care. These methods provide a foundation for automated and standardized burn assessment, improving outcomes across diverse settings.

INTRODUCTION

Burn injuries are a significant cause of morbidity and mortality, particularly in military and disaster settings where timely and accurate assessment is critical for effective clinical management.[1] Early identification of burn depth is essential for guiding surgical planning, and long-term care.[2] For instance, patients with third-degree burns usually need surgery, such as grafting. Second-degree burns tend to heal without surgery but still involve costs, time, and resources. In resource-limited settings, these factors are critical. Misclassifying a third-degree burn as a second-degree burn can worsen the condition and may be life-threatening, specifically when a large area is affected. However, conventional assessment methods relying on clinical expertise are prone to variability, which can delay critical decision-making. Recent advances in artificial intelligence (AI) and computer vision offer promising

[1]Edwardson School of Industrial Engineering, Purdue University, West Lafayette, IN 47907, United States

[2]McGowan Institute for Regenerative Medicine (MIRM), University of Pittsburgh, Pittsburgh, PA 15219, United States

[3]Department of Surgery, University of Pittsburgh School of Medicine, Pittsburgh, PA 15213, United States

[4]Department of Computer Science, Purdue University, West Lafayette, IN 47907, United States

[5]Department of Plastic Surgery, University of Pittsburgh School of Medicine, Pittsburgh, PA 15261, United States

*These authors contributed equally to this work.

Presented as a poster at the 2024 Military Health System Research Symposium, Kissimmee, FL; MHSRS-24-12,580.

The views expressed in this paper are those of the authors and do not necessarily represent the funding institutions.

Corresponding author: Juan P. Wachs, PhD, USA (jpwachs@purdue.edu)

doi:https://doi.org/10.1093/milmed/usaf198

tools to enhance diagnostic precision and efficiency in burn management.

In this study, we propose a comprehensive framework for burn assessment that integrates machine learning techniques, including burn depth classification using Vision Transformer (ViT)[3] (a machine learning method) style transfer-based data augmentation, and zero-shot segmentation with pretrained foundation models. The ViT is a pretrained deep learning model developed using large-scale image datasets. Data augmentation is a method to amplify the number of data points artificially. It enables increased diversity in the training data by introducing variability in the burn wound images. The segmentation task involves separating the burn areas from the nonburn parts of the patient's body. Zero-shot refers to settings where the model is applied to burn wounds for segmentation without having seen them during training. By leveraging these innovative approaches, we address key challenges in burn diagnosis, including limited dataset availability, and the need for scalable, efficient solutions in resource-constrained environments.

Our methods were rigorously tested on a dataset of 131 annotated digital (RGB) images from 29 burn patients, encompassing 3 clinically relevant burn depth classes. To enhance dataset diversity and overcome sample size limitations, we employed data augmentation techniques. Furthermore, we implemented a 2-step zero-shot segmentation approach utilizing GroundingDINO[4] and Segment Anything Model (SAM)[5] to enable precise localization and segmentation of burn regions.

The results demonstrate the potential of these methodologies to significantly advance the field of burn assessment. The ViT model achieved a classification accuracy of 79% in distinguishing 3 burn depth categories, comparable to or exceeding expert-level diagnostic accuracy. The zero-shot segmentation approach effectively identified and delineated burn regions, aligning with clinical expectations and providing a potential and scalable solution for Total Body Surface Area (TBSA) calculation. Style transfer-based data augmentation further enriched the dataset, which has potential to enhance model performance and address the variability inherent in burn injuries.

Overall, this paper highlights the potential of integrating AI-driven approaches into burn care, offering scalable and efficient solutions. Our findings underscore the importance of leveraging machine learning to support medical decision-making, specifically in military and austere environments where rapid and accurate assessments are critical.

BACKGROUND

Burn injuries are among the most complex and challenging conditions encountered in clinical and military settings, often requiring immediate and precise evaluation to guide medical intervention. The severity of burns is determined by depth, which is a critical factor for predicting outcomes and planning treatment. Traditionally, burn depth assessment relies heavily on clinical expertise, which can vary significantly among providers and is influenced by subjective interpretation. This variability can lead to delays in critical decision-making, particularly in high-stress environments such as military or mass casualty settings.

Advanced imaging modalities such as ultrasound and digital imaging have shown promise in enhancing burn assessment, but their implementation is limited by the need for specialized training and equipment.[6–8] Additionally, our study used digital images captured via mobile devices or tablets rather than advanced imaging modalities like ultrasound. Ultrasound requires specialized equipment and expert interpretation, making it less accessible for routine burn assessments. Artificial intelligence and machine learning (ML) offer a transformative opportunity to address these limitations, providing automated, reliable, and scalable solutions to improve burn care.

Burn depth is classified into three main categories based on the extent of damage to the skin layers.[9,10] First-degree burns affect only the epidermis, causing redness without blisters. Second-degree burns extend into the dermis and are further divided into superficial, with blisters and intact dermis, and deep, where the dermis is significantly damaged, but the exact depth is uncertain. Third-degree burns penetrate through the dermis into the hypodermis, often accompanied by eschar, which appears as white, yellow, or black tissue.

Traditional ML and deep learning models have been explored for burn depth diagnosis, but they often require extensive training data to achieve high accuracy.[8] These models typically need millions of samples to learn meaningful features from images, limiting their application in clinical settings, especially in health care areas like burn diagnosis, where obtaining sufficient data is challenging.[11,12] In particular, acquiring high-quality ultrasound data for burns presents significant barriers because of its specialized nature.

A foundation model is a powerful AI system trained on vast amounts of data, allowing it to perform different tasks without needing specialized training for each one. Recent advances in AI-powered image analysis (computer vision) have made it possible to use powerful pretrained AI models for medical imaging. Foundation models are AI systems trained on large amounts of data, allowing them to perform different tasks without extra training. One example is the ViT,[3] which was designed for analyzing text and images and is very good at detecting small details in medical scans, making it useful for assessing burn severity.

Despite these advances, the integration of AI into burn assessment remains underexplored, particularly in high-stakes environments like military medicine. Conventional burn centers rely on subjective human observation and the scarcity of large-scale burn data limits reliable AI model development. Thus, our paper introduces a method that leverages a model pretrained on general image data and fine-tunes it on real burn images to achieve rapid and objective burn

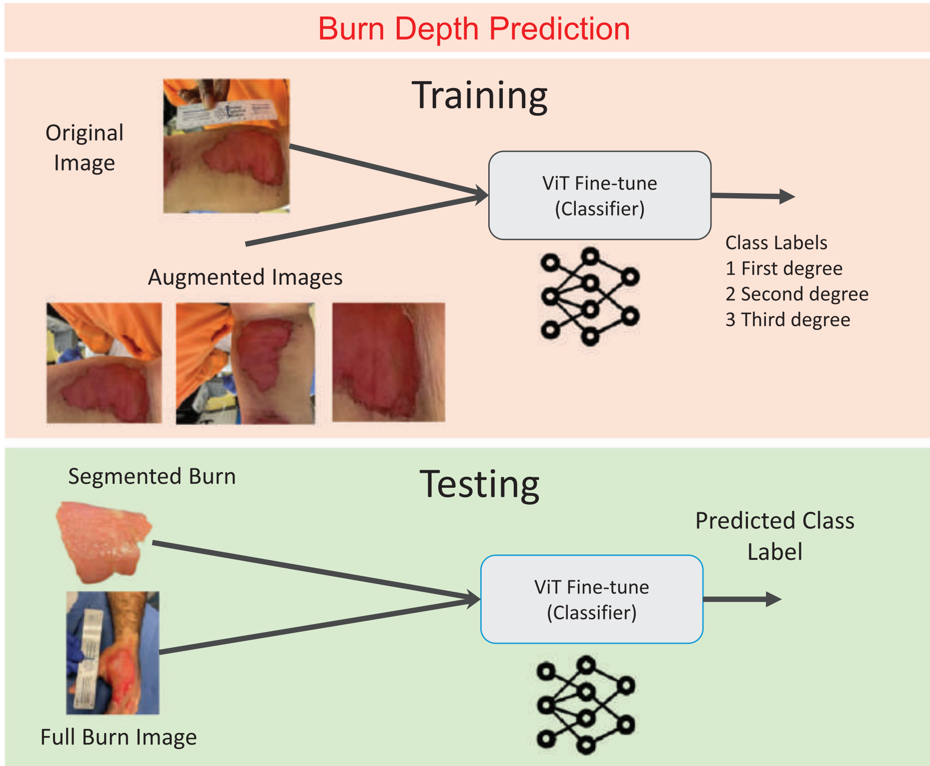

Figure 1. Overview of the proposed Vision transformer-based burn depth prediction model.

diagnosis. This study builds upon existing methodologies to develop a comprehensive framework for burn depth classification and segmentation, leveraging the latest advancements in AI and data augmentation. By addressing the limitations of traditional methods and current AI approaches, this work aims to contribute to the development of scalable, efficient, and clinically relevant tools for burn management in both civilian and military contexts.

MATERIALS AND METHODS

Data Acquisition

We enrolled 30 patients, with one excluded from analysis because of withdrawal, and screened them at the Eskenazi Burn Center, Indianapolis, for eligibility based on inclusion criteria: age 18 years or older, thermal injury within 7 days of the burn, no prior surgical debridement, and burns covering $\leq$75% of TBSA. Exclusion criteria included inability to provide informed consent, age below 18 years, burns $\geq$75% of TBSA, or burns resulting from chemical, electrical, or radiation injuries. To maintain consistency and focus on thermal burns, we excluded burns from chemical, electrical, or radiation injuries because they may require different evaluation protocols; all digital images were acquired using a standardized high-resolution camera system at the burn center. After consent, we captured digital images of the burns using camera which was used in this study.[13] We also imaged unaffected skin from comparable anatomical sites as controls to reduce individual physiological variability in outcome interpretation. This study focuses on analyzing patient's first visit data to enable early prediction of burn depth and enhance clinical decision-making.

To prepare the data for training and evaluating machine learning models, we generated digital annotations and preprocessed the selected dataset.

Burn Depth Prediction with AI (ViT)

We developed a burn depth classification method using a pretrained AI, a ViT model (Figure 1). The ViT processes input images by dividing them into smaller sub-image patches, akin to how transformers handle sequential data in natural language processing, leveraging large-scale pretraining. The model was fine-tuned on a dataset consisting of 131 RGB images obtained from 29 burn patients. These images were annotated with three burn depth classes: First Degree, Second Degree, and Third Degree. Second-degree burns are further categorized into superficial and deep.

To enhance the dataset and mitigate the challenges posed by limited sample size, we applied data augmentation techniques, expanding the dataset from 116 to 1,200 images. Augmented images included variations such as rotations, flips, and brightness adjustments.

Accuracy was used as the primary performance metric. To assess the impact of burn classification granularity, we

Table 1. Results of Burn Depth Prediction

Settings	Cross-validation accuracy (%) Per fold (80% train, 20% test) 1	2	3	4	5	Overall accuracy (%)	Burn specialist
Three-way burn depth classification	80	80	76	84	76	**79**	Burn surgeon 76%, nonexpert 50%
Four-way burn depth classification	65	65	77	80	69	**71**	

The proposed method performs on par with or exceeds the accuracy of evaluations by burn experts.

conducted experiments with 4-class classification and 3-class classification setup, where the 2 types of second-degree burns were merged into a single category. We generated ground truth by having 2 burn experts independently assess each image. In cases of disagreement, the experts reviewed the case together to reach a consensus. The final validation results were then compared against this consensus assessment to ensure accuracy and reliability in our evaluation.

Style Transfer-Based Data Augmentation

To increase the dataset size and diversity, we utilized style transfer techniques. This approach enables the model to learn the visual characteristics of burn injuries and apply them to images of different body parts. For our method, we developed a Cycle Generative Adversarial Network (CycleGAN)[14] that trains a generator model capable of translating images between different burn classes. The training process requires 2 clusters of data, and once trained, the model can perform bidirectional translation between these clusters. Our human data, annotated by experts and categorized into 4 burn classes, was used to define the clusters. For this data augmentation experiment, we focused on two clusters: deep second-degree burns and third-degree burns. The model does not require paired images (e.g., corresponding images of second- and third-degree burns from the same patient), allowing us to use images from different patients within each cluster. This approach eliminates the need for labor-intensive paired image annotation, reducing time and cost.

In our experiment, we utilized 52 images of deep second-degree burns (Class 1) and 31 images of third-degree burns (Class 2) from our dataset. The CycleGAN model was trained on this setup for 200 iterations, with training completed in approximately one hour using a single GPU. During inference, the generator model takes an input image of 1 burn class (e.g., second-degree) and outputs a translated image representing the other burn class (e.g., third-degree) on the same patient and vice versa. This assumes the generator model effectively learns the visual styles associated with different burn types.

Recognition of Burn Areas in New Images after Training (Zero-Shot Segmentation)

Our method uses a 2-step process with pretrained AI models to identify and segment burn regions in images. In the first step, a model called GroundingDINO[4] examines an image together with a text prompt (e.g., "burn region") and identifies a rectangular area that likely contains the burn. In the second step, another model known as Segment Anything Model (SAM)[5] refines this by accurately outlining the burn area within the identified rectangle.

To analyze the total burn area, we also use a query-based approach: the model is prompted with terms like "hand" or "limb" to locate specific body parts, and then with "burn" to segment the affected area. This two-step querying allows us to estimate the TBSA affected by burns. Our evaluation on real human burn data confirms that the integration of these pretrained models offers an efficient and accurate way to segment burn injuries without any additional task-specific training.

Trial Registration: NCT05167461, https://clinicaltrials.gov/study/NCT05167461

RESULTS

Burn Depth Prediction Results

The AI model achieved an average accuracy of 79% for 3-class burn depth classification in the 5-fold cross-validation. Five-fold cross-validation is a method where the dataset is split into 5 folds; in each iteration, 1-fold is used for validation while the remaining 4 folds are used for training. The training was completed on a held-out set, and the model was subsequently tested on a separate held-out validation set.

Data augmentation significantly increased the dataset size, allowing the model to generalize better, but segmentation of burn images (removing backgrounds) did not enhance classification performance. The classifier achieves an overall accuracy of 71% for 4-way burn depth classification. The main challenge in this setting is distinguishing between superficial and deep second-degree burns. Although both are categorized as second-degree burns, the distinction is difficult to discern from digital photographs. This is because deep burns damage the lower layers of the skin, which are not visible in such images. Detailed results are provided in **Table 1**.

Additionally, we explored segmentation to remove background influences and focus solely on burn areas (**Figure 1**); however, this preprocessing step did not improve model performance in this task. Notably, segmentation showed potential utility in specific cases where skin color variation or background artifacts influenced the model's predictions. However, hallucination occurs when an AI model generates incorrect or misleading outputs that are not based on real data. In principle, this method should reduce hallucinations by removing confounding features like the background. Nonetheless, because our dataset consisted mainly of close-up images with the wound centered, we did not observe any significant difference in performance. We believe that in scenarios where a larger portion of the patient's body is captured—especially in austere settings where obtaining high-quality close-up images is challenging—this method could potentially enhance performance.

In comparison to the computation time, the AI model required only a few seconds to generate a diagnosis once training was completed and deployed on a GPU. Meanwhile, burn experts took approximately 2 minutes per case, as they reviewed images from multiple angles to reach a decision. In cases of initial disagreement, the consensus process took up to 3 minutes. Overall, the use of an AI (ViT) for burn depth classification demonstrated promising results, with the potential for further improvement through larger datasets and refined preprocessing techniques.

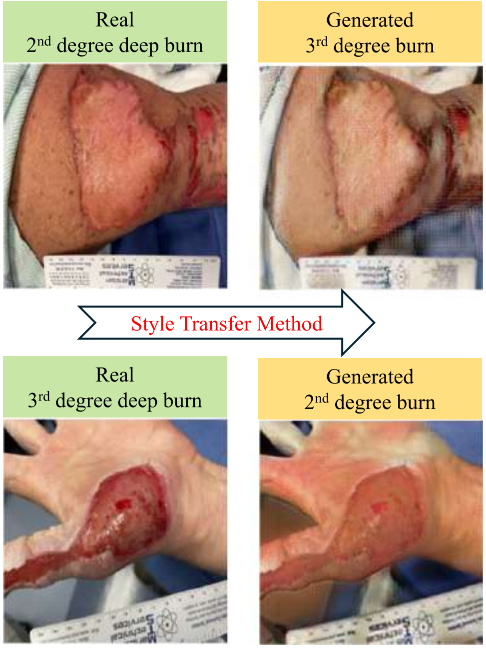

Figure 2. [Top] Left: Real second-degree deep burn. Right: Corresponding generated burn image for third-degree burn. [Bottom] Left: Real third-degree deep burn. Right: Corresponding generated burn image for second-degree burn.

Style Translation Results

The model successfully captured some features of burn types, such as black marks for third-degree burns and reddish tones for second-degree burns, as shown in **Figure 2**. However, the complexity of burn injuries makes it challenging to fully capture all stylistic aspects. For instance, the placement and shape of burns on the body in some generated images appeared unrealistic. While this proof-of-concept experiment demonstrates the model's potential to learn and translate burn features, it also highlights areas for improvement.

Results Analysis of Recognition of Burn Areas in New Images

The method demonstrated accurate segmentation of burn regions, as shown in **Figure 3**, where qualitative results from several examples are provided. A qualitative assessment was performed by two experienced burn surgeons, who confirmed the quality and clinical relevance of the segmentation outputs. The segmentation was evaluated for its ability to accurately delineate burn areas from healthy skin and background, and the surgeons verified that the model's performance aligns with clinical expectations.

The approach successfully localized and segmented burn regions with minimal effort, leveraging natural language prompts to adapt to various scenarios. For instance, initial prompts like "hand" or "limb" allowed the model to focus on specific body parts, followed by the "burn" prompt to identify affected areas within those regions. This hierarchical approach facilitates the precise measurement of TBSA by systematically segmenting burn areas across different body parts.

DISCUSSION

In our burn depth prediction experiments, we leveraged a pretrained AI model (ViT[3]) for burn depth classification. The AI-based model achieved an average accuracy of 79% for the 3-way classification task. This accuracy was computed against the validation set, where the ground truth was verified by burn experts using a consensus mechanism. These results align with the diagnostic accuracy of burn experts,[15] with 70-80% accuracy for experts and 60% for nonspecialists in assessing depth, highlighting the potential of an automated burn assessment system. The nonexperts generally included health care providers, such as Emergency Department (ED) providers, who are often the first to assess burn patients but lack specialized training in burn care. The expert in this context is the burn surgeon. Compared with the burn experts, the AI model generated a diagnosis much faster. In situations where a burn specialist is unavailable, this AI model could provide expert determination of burn depth that would otherwise be unavailable, potentially improving clinical care and treatment outcomes. This underscores the capability of the AI model to capture burn depth-related features, even with a relatively small dataset, and highlights its potential for further improvement with larger, more diverse datasets.

The proposed zero-shot segmentation method, utilizing pretrained foundation models, demonstrates significant potential for clinical and research applications in burn assessment. By combining GroundingDINO and SAM models, the method enables precise identification and segmentation of burn regions with minimal manual intervention, offering a scalable and efficient solution for burn analysis. One of the primary use cases of this approach is in the assessment of burn extent through the automated calculation of

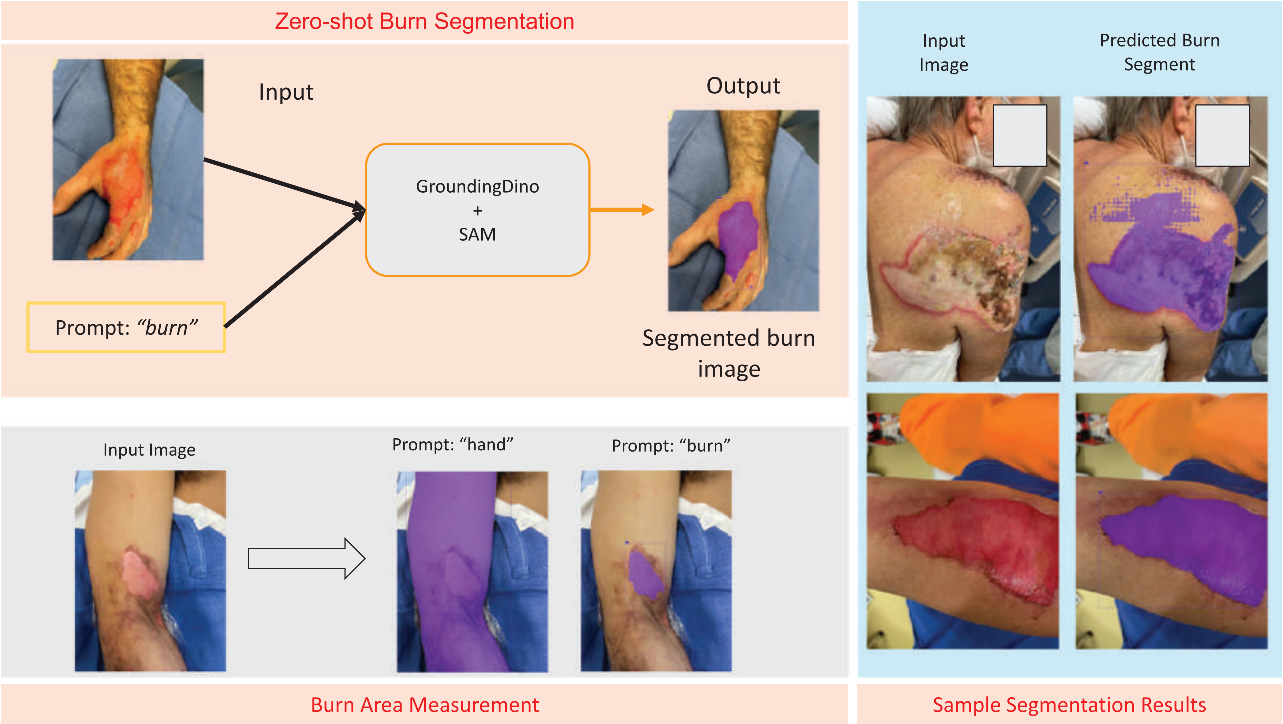

Figure 3. Overview of zero-shot burn segmentation using foundation model.

TBSA. Accurately estimating TBSA is crucial for determining the severity of burn injuries, guiding fluid resuscitation, and planning further medical interventions. The use of natural language prompts to systematically query body parts and burn regions allows for a detailed and consistent analysis, reducing variability introduced by manual estimations.

In addition to segmentation, style transfer-based data augmentation offers potential in burn assessment and machine learning model development. By simulating realistic variations in burn appearance, such as different burn types, depths, or anatomical locations, style transfer can significantly enhance the diversity and representativeness of training datasets. This is particularly valuable in burn assessment, where the availability of comprehensive and diverse datasets is often limited.[16] Style transfer allows the generation of synthetic data that mimics complex burn features, reducing the dependence on large-scale data collection and manual annotation while preserving clinical relevance. These augmented datasets can improve the generalizability and robustness of machine learning models for tasks such as burn depth classification, segmentation, and outcome prediction.

Despite these promising applications, there are limitations to consider. The accuracy of segmentation and burn depth classification may vary depending on the quality of input images and the diversity of the training data for the foundation models. While qualitative validation by burn surgeons confirmed the reliability of segmentation, quantitative validation on larger datasets is necessary to fully assess the method's robustness and generalizability. Similarly, while style transfer demonstrates strong potential for augmenting datasets, ensuring the clinical fidelity of synthetic data and addressingpotential biases in generated images remain challenges for future research.

In summary, the proposed method uses advanced AI models, called Vision Transformers, to predict how deep a burn is, showing promising results. It also improves the accuracy of these predictions by using a technique called style transfer to create more varied training images for the AI. By tackling major challenges in burn assessment, this approach provides a faster, more reliable, and adaptable way to analyze burns, making it a valuable tool for medical professionals.

Future work will focus on increasing the quantity and diversity of training data to better represent various burn types and refine the style transfer model. We aim to investigate enhancements that generate more realistic and clinically useful burn images. For instance, incorporating photos of burn patients taken under different lighting conditions could provide a more robust evaluation of the system's ability to grade burn severity. Additionally, we will further explore the impact of lighting variations. In summary, augmenting RGB image data for burn injuries is a critical step in building a more robust and comprehensive dataset to support ongoing efforts in burn segmentation and multimodal diagnostic systems for human burn assessment.

CONCLUSION

This study demonstrates the potential of integrating advanced machine learning methods and data augmentation techniques into burn depth assessment. By leveraging an AI model, we achieved promising accuracy in burn depth classification. The model's ability to classify burns into clinically relevant categories highlights its potential for enhancing diagnostic precision and supporting clinical decision-making.

The incorporation of style transfer-based data augmentation successfully enriched the dataset, simulating realistic variations in burn appearances. Meanwhile, the use of zero-shot segmentation method with foundation models demonstrated the capability of AI systems to localize and segment burn regions effectively. These approaches minimize the need for extensive manual intervention, making them scalable and practical for deployment in diverse clinical environments. In conclusion, our findings highlight the transformative potential of AI-driven approaches in burn care. By addressing the limitations of traditional methods and current AI implementations, this study contributes to the development of reliable, scalable, and efficient tools for improving outcomes in burn management, particularly in high-stakes environments such as military and disaster medicine.

ACKNOWLEDGMENTS

We thank Brett C. Hartman, MD, and Leigh Spera, MD, for their contributions and assistance in facilitating data collection on burn patients.

FUNDING

This work was supported by the Office of the Assistant Secretary of Defense for Health Affairs under Award No. W81XWH-21-2-0030 and by NIH under Grant No. 5R21LM013711-02.

SUPPLEMENT SPONSORSHIP

This article appears as part of the supplement "Proceedings of the 2024 Military Health System Research Symposium," sponsored by the Assistant Secretary of Defense for Health Affairs.

CONFLICT OF INTEREST STATEMENT

None declared.

DATA AVAILABILITY

The data are available upon reasonable request to the corresponding author.

INSTITUTIONAL REVIEW BOARD (HUMAN SUBJECTS)

The study protocol and experimental procedures were reviewed and approved by the institutional review board (IRB# 12,689) at Indiana University. All patients provided consent to participate in the study according to the IRB protocol and the Declaration of Helsinki guidelines.

INSTITUTIONAL ANIMAL CARE AND USE COMMITTEE (IACUC)

Not applicable.

INSTITUTIONAL CLEARANCE

Not Applicable.

INDIVIDUAL AUTHOR CONTRIBUTION STATEMENT

Conceptualization and design; M.E., G.G., and J.W.; Investigation and Validation: M.M.R., M.E., S.G., Y.X., G.G., and J.W.; Data Analysis: M.M.R., M.E., and S.G.; Writing: M.M.R., M.E., G.G., and J.W.; Review: M.M.R., M.E., S.G., Y.X., G.G., and J.W.; Funding Resources: G.G. and J.W.

CLINICAL TRIAL REGISTRATION

FNCT05167461, https://clinicaltrials.gov/study/NCT05167461

REFERENCES

1. Anyanwu JA, Cindass R. Burn Debridement, Grafting, and Reconstruction, *StatPearls [Internet]*. StatPearls Publishing; 2023.
2. Finnerty CC, Jeschke MG, Branski LK, et al. Hypertrophic scarring: the greatest unmet challenge after burn injury. *Lancet*. 2016; 388(10052):1427–36.
3. Dosovitskiy A, Beyer L, Kolesnikov A, et al An image is worth 16x16 words: transformers for image recognition at scale. In: *International Conference on Learning Representations*; 2021. https://openreview.net/forum?id=YicbFdNTTy
4. Liu S, Zeng Z, Ren T, et al. Grounding dino: marrying dino with grounded pre-training for open-set object detection. *arXiv preprint arXiv:230305499*. Published online 2023.
5. Kirillov A, Mintun E, Ravi N, et al. Segment anything. In: *Proceedings of the IEEE/CVF International Conference on Computer Vision*; 2023:4015–26.
6. Jacobson MJ, El MM, Arrubla DC, et al. Autonomous Multi-modality burn wound characterization using artificial intelligence. *Mil Med*. 2023; 188(Supplement_6):674–681. 10.1093/milmed/usad301
7. Wang Y, Ke Z, He Z, et al. Real-time burn depth assessment using artificial networks: a large-scale, multicentre study. *Burns*. 2020; 46(8):1829–38. 10.1016/j.burns.2020.07.010
8. Cirillo MD, Mirdell R, Sjöberg F, Pham TD. Time-independent prediction of burn depth using deep convolutional neural networks. *J Burn Care Res*. 2019; 40(6):857–63.
9. Browning J, Island RC, Fsp LLC, 2022 undefined. Burn debridement, grafting, and reconstruction. *europepmc.org*. Accessed July 11, 2024. https://europepmc.org/books/n/statpearls/article-18722/?extid=32491406&src=med
10. Abazari M, Ghaffari A, Rashidzadeh H, Badeleh SM, Maleki Y. A systematic review on classification, identification, and healing process of burn wound healing. *Int J Low Extr Wound*. 2022; 21(1):18–30. 10.1177/1534734620924857/ASSET/IMAGES/LARGE/10.1177_1534734620924857-FIG4.JPEG
11. Martins JFBS, Nascimento ER, Nascimento BR, et al. Towards automatic diagnosis of rheumatic heart disease on echocardiographic exams through video-based deep learning. *J Am Med Inform Assoc*. 2021; 28(9):1834. 10.1093/JAMIA/OCAB061
12. Boissin C, Laflamme L, Jian F, et al. Development and evaluation of deep learning algorithms for assessment of acute burns and the need for surgery. *Sci Rep 2023 13:1*. 2023; 13(1):1–9. 10.1038/s41598-023-28164-4
13. Sen CK, Ghatak S, Gnyawali SC, Roy S, Gordillo GM. Cutaneous imaging technologies in acute burn and chronic wound care. *Plast Reconstr Surg*. 2016; 138(3 Suppl):119S.
14. Armanious K, Jiang C, Abdulatif S, et al. Unsupervised medical image translation using Cycle-MedGAN. In: *2019 27th European Signal Processing Conference (EUSIPCO)*. IEEE; 2019:1–5.
15. Thatcher JE, Squiers JJ, Kanick SC, et al. Imaging techniques for clinical burn assessment with a focus on multispectral imaging. *Adv Wound Care*. 2016; 5(8):360–78.
16. Huang S, Dang J, Sheckter CC, Yenikomshian HA, Gillenwater J. A systematic review of machine learning and automation in burn wound evaluation: A promising but developing frontier. *Burns*. 2021; 47(8):1691–704. 10.1016/j.burns.2021.07.007