REST Journal on Data Analytics and Artificial Intelligence
Vol: 3(2), June 2024
REST Publisher; ISSN: 2583-5564
Website: http: //restpublisher.com/journals/jdaai/
DOI: https://doi.org/10.46632/jdaai/3/2/14

Provisional Diagnosis and Prognosis of Burn Skin Using Convolutional Neural Network

*** J. Mary Hanna Priyadharshini, Priyadharshni T, Sowmiya S, Preethi L**
Vel Tech High Tech Dr. Rangarajan Dr. Sakunthala Engineering College
Chennai, India
**Corresponding author: hannapriyadharshini@gmail.com*

Abstract: *This paper explores the use of a convolutional neural network (CNN) in burn skin diagnosis and prognosis. Leveraging a variety of labelled medical images, the model integrates to acquire comprehensive features. By enhancing diagnostic and prognostic accuracy, the model aims to boost the outcomes of dermatological care. When compared to conventional techniques, the CNN performs better for provisional diagnosis, obtaining high accuracy in classifying burn severity. By estimating possible outcomes based on the original evaluation, the model is further expanded to offer a prediction of the healing process. In relation to treatment plans and long-term patient care, this expertise allows plastic surgeons to make informed decisions. Considering consideration of different clinical settings and patient demographics, we assess the suggested method on an extensive dataset of burn skin photos. The outcomes demonstrate that the CNN can diagnose and predict burn skin damage. Our results imply that using advanced deep learning methods in the plastic surgery workflow can greatly improve the accuracy and effectiveness of burn-related analyses.*

Keywords: *Burn Skin, Plastic Surgery, Convolutional Neural Network, Multi-Channel, Imbalanced Data.*

1. INTRODUCTION

Plastic surgery plays a pivotal role in restoring form and function to damaged skin resulting from burns. However, accurate diagnosis and prognosis of the outcomes of such interventions remain intricate challenges, requiring a nuanced understanding of the diverse manifestations of these skin conditions. In the pursuit of improving the precision of diagnostic and prognostic processes, this research investigates the application of convolutional neural networks (CNNs), a state-of-the-art technology in artificial intelligence, in the domain of plastic surgery. The motivation behind this study emanates from the inherent complexities associated with interpreting and analyzing medical images in the context of plastic surgery. Traditional methods often fall short of consistently providing the level of accuracy required for effective clinical decision-making. With the advent of CNNs, which excel in image recognition tasks, there is a promising avenue to significantly enhance the capabilities of medical professionals in the provisional diagnosis and prognosis of skin conditions resulting from burns. Dataset Acquisition to train and evaluate the Convolutional Neural Network (CNN), a comprehensive dataset of medical images depicting skin conditions resulting from burns was meticulously curated. The dataset comprises a diverse range of cases to ensure the model's robustness and generalizability. Images were sourced from reputable medical databases, ensuring ethical considerations and patient confidentiality. The CNN model was trained using a labelled subset of the curated dataset. The training process involved iterative optimization of the model's weights using a well-established optimization algorithm. The model was fine-tuned to minimize a predefined loss function, and training hyper parameters, such as learning rate and batch size, were optimized through experimentation.

2. RELATED WORKS

The application of convolutional neural networks (CNNs) to medical image analysis has garnered a lot of interest, especially in the dermatology area. In this field, Esteva et al. (2017) were pioneers, showing that a CNN could classify skin cancer with an accuracy that was on par with dermatologists. The CNN effectively identified between benign and malignant lesions after being trained on a sizable dataset of dermoscopic pictures, demonstrating the potential of CNNs to completely transform the accuracy of diagnosis in dermatological practice. Goyal et al.

(2018) created a CNN-based paradigm to evaluate the severity of burn wounds in the context of burn diagnosis. Their model fared better in classifying burn severity than conventional image processing methods after being trained on a large dataset of burn photos. This study highlights the unique benefits of CNNs in the analysis of intricate skin disorders, offering a reliable instrument to enhance burn treatment diagnostic accuracy. Besides dermatological and burn diagnostics, CNNs have proven useful in other medical imaging fields as well. For example, Yudong et al. (2016) used CNNs with stationary wavelet entropy (SWE) to automatically diagnose Alzheimer's disease from magnetic resonance imaging (MR). Although their main area of interest was brain imaging, the technique of fusing CNNs with sophisticated feature extraction can be modified to improve burn injury diagnosis. In order to enhance classification performance, Kim et al. (2016) emphasized the significance of structured feature selection in CNN models. CNNs may extract hierarchical characteristics that considerably improve diagnostic accuracy, as evidenced by their work on the diagnosis of schizophrenia using resting-state functional connectivity patterns. By using feature selection techniques to identify the important details in burn photos, this method can be applied to the diagnosis of burns and result in assessments that are more precise. To sum up, the use of CNNs to medical image processing presents a viable way to improve prognostic and diagnostic accuracy, especially in the area of burn diagnosis. Through the use of CNNs' advantages in image identification and feature extraction, these models offer physicians strong instruments that facilitate enhanced decision-making and better patient outcomes in the field of burn care. The developments in CNN-based techniques highlight the possibility for additional improvements in the area, opening the door for more effective and efficient diagnostic

3. METHODOLOGIES

We developed the first convolutional neural network (CNN) to identify and categories patient burn injuries with the goal of enhancing dermatological and plastic surgery diagnostic procedures. There is no copyright violation and our collection, which includes 1,100 photos of burn injuries, was gathered from a variety of sources, including Google. The dataset, which included an uneven distribution of photos across various burn severity classes, was divided into 90% for training and 10% for validation.

3.1 Data Collection and Preprocessing:

The images in the dataset were categorized into four classes based on burn severity:

- Degree 1: Mild skin burn with tan
- Degree 2: Moderate burns with blisters
- Degree 3: Severe burns recommended for plastic surgery
- Healthy Skin: No burns

The dataset was carefully chosen to ensure an inclusive representation of burn injuries. Degree 1 and Degree 2 burns had more images, while Degree 3 burns and healthy skin had fewer images, reflecting the imbalance often found in real-world medical datasets. Pre-processing steps included:

1. Removing Duplicates: assure unique images in the dataset.
2.Irrelevant Data: Focusing on the burn areas to provide the CNN with relevant features.
3.No Additional Filtering: Unlike traditional methods, no filtering techniques were applied, preserving the original image characteristics in order to predict the real image of patients.

3.2 CNN Architecture:

Our CNN model was designed with multiple convolutional layers to effectively extract features from the burn images. The architecture is as follows:

1. Input Layer: Accepts images of size 128x128 with 3 color channels (RGB).
2.Convolutional Layers:

  ◦ First layer with 32 filters, kernel size (3x3), activation function 'ReLU'.
  ◦ Second layer with 64 filters, kernel size (3x3), activation function 'ReLU'.
  ◦ Third layer with 64 filters, kernel size (3x3), activation function 'ReLU'.
  ◦ Fourth layer with 96 filters, kernel size (3x3), activation function 'ReLU'.
  ◦ Fifth layer with 32 filters, kernel size (3x3), activation function 'ReLU'.

3. Pooling Layers: To minimize spatial dimensions, MaxPooling2D layers are utilized after each convolutional layer.
4. Batch Normalization: Applied after each pooling layer to normalize outputs and speed up training.
5. Dropout: Applied with a rate of 0.2 after the last convolutional layer and 0.3 before the final dense layer to prevent overfitting.

6. Flatten Layer: Converts the pooled feature maps into a single feature vector.
7. Dense Layers:
    - First dense layer with 128 neurons and 'ReLU' activation.
    - Output layer with 4 neurons (corresponding to the four classes) and 'softmax' activation for classification

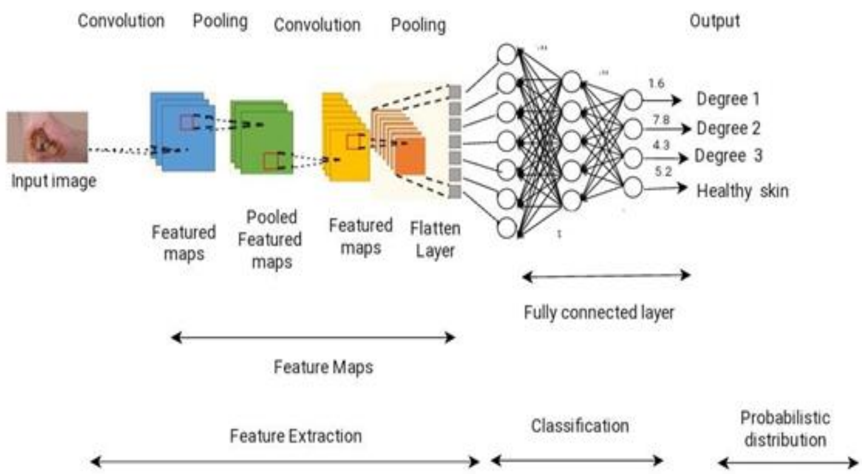

FIGURE. 1

3.3 Soft max Function:

Especially for multi-class issues like burn injury classification, the soft max function plays a critical role in the last layer of a classification neural network. It facilitates result interpretation by converting the network's raw output scores into probabilities that add up to 1

For a given collection of logits □ = [□ 1 ,□ 2 ,...,□ □] z=[z 1,z 2,...,z k], the soft max function is defined as follows:

$$softmax(z_i) = \frac{exp(z_i)}{\sum_j exp(z_j)}$$

3.3.1 Interpreting the Output:

The vector of probabilities represented by P= [P 1, P 2, P 3, P 4] is the output of the soft max function. The likelihood that the input image corresponds to the associated class is shown by each element P I.

For example, *P* 1 P 1 = likelihood of a first-degree burn,

□ 2 P 2 = likelihood of a second-degree burn,

□ 3 P 3 = likelihood of a third-degree burn,

□ 4 P 4 = likelihood of healthy skin.

4. PREDICTION

A sturdy convolutional neural network (CNN) model for diagnosing and classifying burn injuries based on severity. Moving forward, our research will focus on expanding the capabilities of this model to provide actionable recommendations for treatment based on the degree of the burn. This improvement aims to not only diagnose but also guide appropriate medical response, integrating these recommendations into a user-friendly graphical user interface (GUI).

Enhanced Predictions and Recommendations
1.First-Degree Burns: For burns categorized as first-degree, the model will recommend basic first aid treatments. These recommendations may include cooling the burn under running water, applying aloe Vera or moisturizer, in order to taking over-, the pain. The aim is to provide immediate, reachable care advice to minimize discomfort and promote healing.
2.Second-Degree Burns: For second-degree burns, which involve deeper skin layers and blisters, the model will advise seeking medical attention. The recommendations will include initial first aid steps similar to those for first-degree burns, followed by an immediate response to consult a healthcare professional to prevent complications and ensure proper healing.
3.Third-Degree Burns: For the most severe burns, categorized as third-degree, the model will strongly recommend seeking specialized medical care, particularly from plastic surgeons. These burns often require advanced medical interventions, including surgery. The recommendations will emphasize the urgency of professional medical treatment to manage pain, prevent infections, and start reconstructive processes if necessary.
4.Healthy Skin: if images were classified as healthy skin, they would provide the recommendations for maintaining a skin health, such as proper hydration, the use of sunscreen, cleansing to Remove dirt, oil from the skin and regular moisturizing, and in-taking a food in order to balance diet including vitamins, fiber.

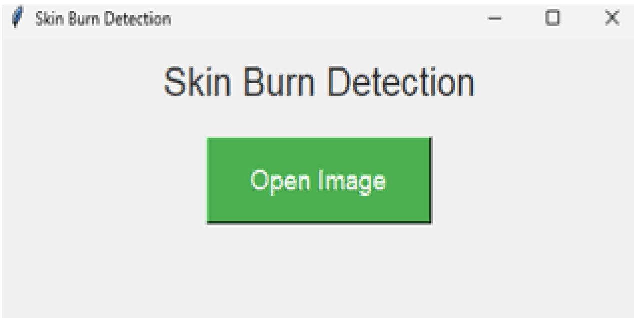

FIGURE. 2

FIGURE. 3

FIGURE. 4

5. CONCLUSION

In conclusion, this research utilizes the power of Convolutional Neural Networks (CNNs) to significantly improve the provisional diagnosis and prognosis of skin conditions in the context of plastic surgery, particularly those resulting from burns. The strong performance of the CNN, as evidenced by accuracy, underscores its potential as a valuable tool in clinical decision-making. the study marks a notable advancement, it is crucial to acknowledge its limitations, particularly the scope of the dataset(imbalance). Handling imbalanced datasets using convolutional neural networks (CNNs) is in fact challenging. The ongoing clarification of the model and expansion of the dataset improve the CNN's generalizability. Strongest candidates for practical deployment in plastic surgery intrusion are the model's capacity for real-time clinical applications and its ability to generalize across a variety of circumstances. Clarifying the model and guaranteeing its integration into clinical operations will require ongoing collaboration between data scientists and medical experts. In a way, this study advances the rapidly evolving field of artificial intelligence in medicine by serving as a useful diagnostic and prognostic tool for skin disorders in plastic surgery, ultimately leading to better patient outcomes.

REFERENCES

[1]. Machine Learning Demonstrates High Accuracy for Disease Diagnosis and Prognosis in Plastic Surgery Angelos Mantelakis t al. Plast Reconstr Surg Glob Open. 2021.Free PMC article Hide details Plast Reconstr Surg GlobOpen.2021Jun24;9(6): e3638.doi:10.1097/GOX.0000000000003638. Collection 2021 Jun. Authors Angelos Mantelakis 1, Yannis Assael 2, Parviz Sorooshian3, Ankur Khajuria 4 Affiliations1Department of Surgery and Cancer, Imperial College London, UK.2University of Oxford, UK.3Queen Victoria Hospital, UK.4Kellogg College, University of Oxford.PMID: 34235035PMCID:PMC8225366DOI:10.1097/GOX.00000000000036 3.

[2]. Chapter: Chapter 10 Local plastic surgery-based face recognition using convolutional neural networks Book: Demystifying Big Data, Machine Learning, and Deep Learning for Healthcare Analytics Author: Roshni Khedgaonkar, Kavita Singh, Mukesh Raghuwanshi Publisher: Elsevier Date: 2021 https://doi.org/10.1016/B978-0-12 821633-0.00001-5.

[3]. Applications of Machine Learning in Facial Cosmetic Surgeries: A Scoping Review 2023 Aug;47(4):1377-1393 doi: 10.1007/s00266-023-03379-y Epub 2023 Jun Authors Nima Ahmadi 1 2, Maral Niazmand 1 2, Ali Ghasemi 1 2, Sadra Mohaghegh 1 2, Saeed Reza Motamedian 3.

[4]. A Narrative Review of Artificial Intelligence (AI) for Objective Assessment of Aesthetic Endpoints in Plastic Surgery 2023 Mar 31doi: 10.1007/s00266-023-03328

[5]. Applications of Artificial Intelligence, Machine Learning, and Deep Learning on Facial Plastic Surgeries. In: Cosmetic and Reconstructive Facial Plastic Surgery. Springer, Cham. https://doi.org/10.1007/978-3-031-31168-0_9 Published 27 June 2023.Published online 2021 Jun 24. Doi: 10.1097/GOX.0000000000003638 PMCID: PMC8225366PMID: 34235035.

[6]. Potential for Machine Learning in Burn Care https://doi.org/10.1093/jbcr/irab189 Published: 13 October 2021.

[7]. Implementing AI Models for Prognostic Predictions in High-Risk Burn Patients. Diagnostics 2023, 13, 2984 https://doi.org/10.3390/diagnostics13182984.

[8]. Published online 2022 Oct 7. Doi: 10.1097/MD.0000000000030943 PMCID: PMC9542809PMID: 36221333 The use of machine learning for investigating the role of plastic surgeons in anatomical injuries: A retrospective observational study.

[9]. Artificial Intelligence in Dermatology Image Analysis: Current Developments and Future Trends. J. Clin. Med. 2022, 11, 6826. https://doi.org/10.3390/jcm11226826

[10]. Published online 2023Aug18.doi:10.1038/s41598-023 4039PMCID:PMC10439171PMID: 37596459 Predicting the severity of postoperative scars using artificial intelligence based on images and clinical data.

[11]. Update on Postsurgical Scar Management PMID: 27478420 PMCID: PMC4961501 DOI: 10.1055/s-0036-1584824.

[12]. Artificial intelligence in the management and treatment of burns: a systematic review https://doi.org/10.1093/burnst/tkab022 Published: 19 August 2021. 20 [13]

[13]. Computer-aided diagnosis for burnt skin images using deep convolutional neural network December 2020Multimedia Tools and Applications 79(45-46) DOI:10.1007/s11042-020-08768-y.

[14]. Implementing AI Models for Prognostic Predictions in High Risk Burn Patients. https://doi.org/10.3390/diagnostics13182984

[15]. Feature Extraction Based Machine Learning for Human Burn Diagnosis from Burn Image Published online 2019 Jul 18.doi:10.1109/JTEHM.2019.2923628

