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Research Article

Development a software for detecting burn severity using convolutional neural network-based approach

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ABSTRACT

Burns are a significant cause of injury and can result in severe physiological reactions, metabolic disturbances, scarring, organ failure, and even death if not properly managed. Traditional clinical methods for assessing burn severity can be challenging due to various factors. In the event of a burn incident, an AI-based application can quickly analyse large amounts of data, expedite repetitive tasks like burn severity assessment, reduce subjective human errors, provide a more objective evaluation of burn severity, become more accessible in areas lacking expert medical personnel or during emergencies, and offer information-based treatment options. To address this issue, this study proposed a Deep Convolutional Neural Network (DCNN) approach to detect the severity of burn injury using real-time images of skin burns. Deep learning (DL) algorithms, namely GoogleNet, ResNet-50, and Inception-v3, were employed to train the images in Matlab software. In addition, almost 25% of the images were reserved for external validation. The developed interface achieved an accuracy rate of 90.22% in assessing burn severity based on visual data from actual cases. Consequently, by harnessing intelligent technologies, the suggested DCNN-based method can assist healthcare professionals in assessing the extent of burn injuries and delivering timely and suitable treatments. This, in turn, significantly mitigates the adverse outcomes associated with burns.

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INTRODUCTION

Trauma refers to a sudden event resulting from the mechanical impact of an external factor during an incident or accident, leading to physical and psychological harm to individuals [1]. Conversely, a wound involves the disruption of the skin or mucous membrane layer's integrity due to the effects of trauma [2]. Burn injuries constitute a major public health concern worldwide, given their potential to induce severe physiological repercussions, metabolic imbalances, lasting scars, organ dysfunction, and even fatality when not managed effectively [3]. Traditional clinical methods employed to assess the severity of burns often encounter formidable challenges, owing to the complex

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nature of burn injuries. Burn injuries, which are characterized by skin damage caused by various factors like heat, chemicals, electricity, or radiation, constitute a specific type of wound. Each year, approximately 1.25 million individuals in the United States seek medical attention for burn-related issues, with roughly 50,000 of these cases receiving treatment and being discharged [4].

Harish et al. [5] demonstrated that administering conscious basic first aid for burns is associated with positive clinical outcomes, including the reduction of burn depth and shorter recovery times. Tay et al. [6] reported that healthcare workers often possess limited knowledge of burn first aid, but participation in a burn first aid course significantly enhances their understanding. They recommended revising the content of first aid courses to include topics related to burns and encouraged all hospital healthcare workers to undergo such training. Graham et al. [7] found that awareness among families regarding first aid for burns is generally low, particularly concerning proper cooling durations and concerns about using the appropriate dressing methods.

Machine learning involves the use of algorithms to transform inputs into outputs through statistically derived, data-based rules, without the need for explicit instructions from humans. Deep learning, a subset of machine learning, entails training machines on raw data to develop their representations, typically composed of multiple layers [8]. Characterized by the rapid processing of immense volumes of data, deep learning algorithms are utilized to extract a multitude of parameters from billions of data points, thereby enabling the resolution of a wide array of challenges [9]. Deep learning finds extensive application across various fields, including computer vision and natural language processing [10]. The use of deep learning algorithms in image processing has yielded successful results, simplifying the resolution of complex image processing problems [11]. Given its significant advancements and outstanding performance in various applications, deep learning is widely adopted in various domains, encompassing business, science, adaptive testing, biological image classification, computer vision, cancer detection, natural language processing, object detection, face recognition, handwriting recognition, speech recognition, stock analysis, smart cities, and more [12].

In dermatology, deep learning plays a fundamental role in clinical tasks such as specific differential diagnosis of lesions, identification of relevant lesions among numerous benign ones, and monitoring lesion growth over time [13]. Several studies have demonstrated that Convolutional Neural Networks (CNNs) can match the performance of board-certified dermatologists in distinguishing malignant skin lesions from benign ones. However, these studies are primarily focused on binary classification tasks, including distinguishing between benign and malignant skin lesions and melanomas, or seborrheic keratoses and carcinomas [14].

Deep learning is a widely used technique in the field of artificial intelligence, and it has the potential for applications in various domains [15]. It is employed in many different disciplines, including image and speech processing, natural language processing, automotive industry, finance, manufacturing, robotics, medical science and optimization [16-18]. In the field of medicine, deep learning finds applications in disease diagnosis, medical image processing, drug discovery, genetic analysis, disease prognosis, disease management, and treatment planning [19].

In the medical field, deep learning methods have the potential to be used for diagnosing burns, assessing various factors related to burns such as burn severity, size, the cause of the burn, and the healing process [20]. Khan et al. [21] focused on classifying wounds into 1st, 2nd, and 3rd-degree burns through Deep Convolutional Neural Network methods. Chauhan and Goyal [22] developed a deep convolutional neural network model to evaluate burn severity across body parts like the face, hand, back, and inner forearm, using ResNet50, VGG16, and VGG19 networks. In their subsequent work of Chauhan and Goyal [23], they utilized the ResNet-101 model for burn region segmentation. Suha and Sanam [24] explored various classification models—Logistic Regression, K-Nearest Neighbor, Support Vector Machine, Decision Tree, Random Forest, and Multilayer Perceptron—to assess burn severity, where the Random Forest classifier achieved the highest accuracy of 80%. However, up to this point, there hasn't been a comprehensive study that includes developing burn classification software and the creation of appropriate treatment plans for burn cases [25, 26].

This study employs three distinct deep learning architectures—GoogleNet, ResNet-50, and Inception-v3—to assess and classify the severity of burn injuries. Each of these models is designed to extract and analyze complex features from medical images, enabling accurate detection and differentiation of burn injury severity levels. GoogleNet, known for its inception modules that enhance computational efficiency, effectively captures both low- and high-level image features. ResNet-50, a residual network with 50 layers, excels in overcoming vanishing gradient issues through its skip connections, improving deep feature extraction. Meanwhile, Inception-v3, an advanced version of the Inception network, optimizes both depth and width for enhanced performance in image recognition tasks. By leveraging these three architectures, the study aims to improve diagnostic accuracy and provide reliable assessments of burn injury severity.

MATERIALS AND METHODS

This work is structured around five principal stages (illustrated in Figure 1): (i) gathering burn images and performing image augmentation, (ii) assessing the severity of burns, (iii) applying artificial intelligence frameworks to train the collected pictures, (iv) creating a user freandly software, and (v) evaluating and validating the software's results. Detailed explanations of each stage are provided in the subsequent subsections.

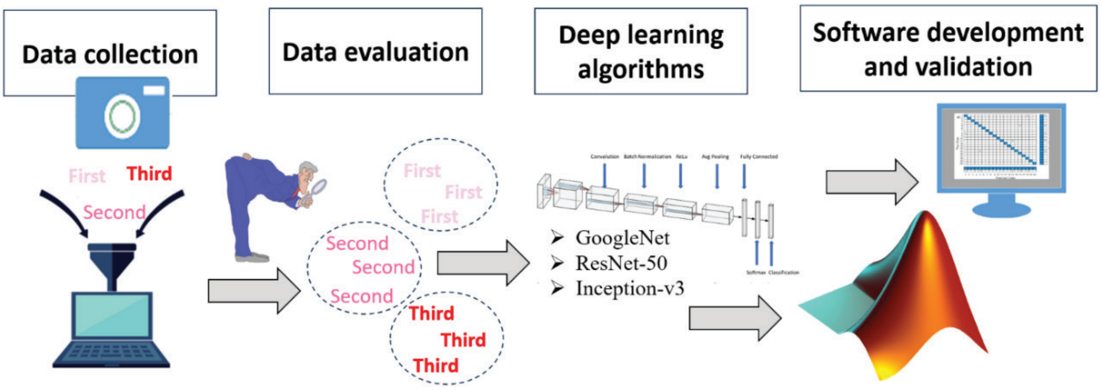

Figure 1. Process of developing prediction software.

Collection of Burn Images

This research utilized digital colour images of skin burns, with the dataset containing 2301 images in total. Out of these, 1201 images were obtained from publicly accessible images via Google search, and the rest were sourced from the burn dermatology atlas, various books, and genuine case data. The images derived from actual cases were photographed with digital cameras from three different mobile phones, under ideal lighting conditions to guarantee high image clarity. This approach enabled precise distinction between burned and unburned areas, as well as the surrounding environment.

The images in this study were classified into three severity categories: first-degree, second-degree, and third-degree burns, with the categorization conducted under the guidance of three healthcare professionals, one of whom is a specialist doctor. Images of first-degree burns show minimal damage, whereas images of third-degree burns display severe damage. The dataset includes 574 images of first-degree burns, 834 images of second-degree burns, and 893 images of third-degree burns.

As all the input digital images are in RGB format, each one comprises three channels. However, due to their varied origins, the images come in different formats and sizes, which are not conducive to predictive analytics as is. To remedy this, all images were standardized to a consistent size of (224 × 224 × 3), denoting the image's row, column, and channel dimensions, respectively. As a size criterion, images with minimum 224 × 224 pixels were used. At this point 1594 images remained for further processing. Following resizing, these images were organized into a 3D multichannel array. Additionally, the labels for each image were compiled into a one-dimensional array, acting as the target variable for the machine learning stage. Figure 2 displays an example image from each burn severity category.

According to Buslaev et al. [27], image augmentation is a powerful technique widely employed in computer vision and deep learning to expand the size and diversity of a training dataset through artificial means. This method involves applying various transformations to existing images, including rotations, translations, flips, zooms, shearing effects, and color adjustments, as highlighted by reference [28]. By generating multiple modified versions of the original images, this technique effectively increases the dataset's variability. Consequently, image augmentation enhances the model's ability to generalize better to unseen data, improving its robustness and reducing the risk of overfitting. This approach is particularly advantageous in scenarios where collecting a sufficiently large dataset is impractical or when the available data is limited.

In the training phase, applying random transformations to images broadens the spectrum of variations the model encounters, forcing it to identify and learn more robust features. This approach is aimed at reducing the risk of overfitting and improving the model's ability to perform well with new, unseen data. In our research, we adopted image

Figure 2. Example of first, second and third degree burnt input images.

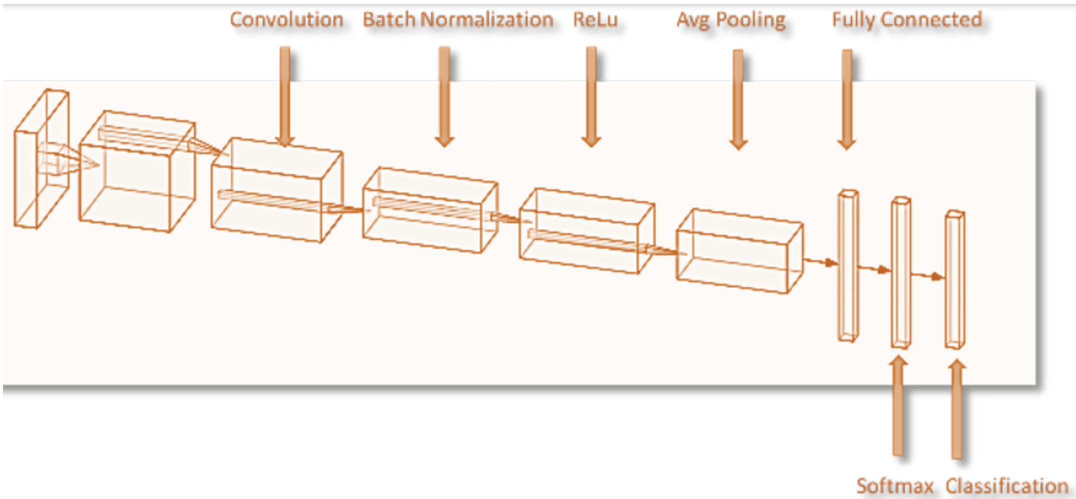

Figure 3. Fundamental building blocks of applied deep learning models.

augmentation strategies by randomly executing rotations, translations, flips, zooms, and colour modifications. This method effectively quadrupled the dataset size from its original number of images.

Deep Learning Algorithms

Deep learning, a subset of machine learning methods, enables computers to learn and perform tasks by using artificial neural networks to identify meaningful patterns within data, as highlighted by França et al. [29]. These networks are made up of multiple connected layers that perform complex calculations in parallel, similar to the human nervous system, as described by Dongare et al. [30]. With extensive training on large datasets, deep learning models achieve exceptional accuracy in various tasks, such as object recognition, often outperforming human capabilities. In our research, we leveraged three specific deep learning algorithms available in Matlab's deep learning toolbox: GoogleNet, ResNet-50, and Inception-v3, which contain 22, 50, and 48 layers, respectively. The key elements of these neural network architectures are illustrated in Figure 3.

Assessment of Training and Validation Performance

In the context of classification problems, evaluating a classifier's performance frequently involves the examination of the associated confusion matrix. Additionally, it is feasible to compute various metrics, namely Average accuracy, Error rate, Precision, Recall, and F-score, by employing equations (1), (2), (3), (4), and (5) respectively, which are derived from the values within the matrix, as outlined by Sokolova and Lapalme in 2009 [31].

$$Average\ accuracy = \frac{\left(\sum_{i=1}^{l} \frac{tp_i + tn_i}{tp_i + fn_i + fp_i + tn_i}\right)}{l} \tag{1}$$

$$Error\ rate = \left(\sum_{i=1}^{l} \frac{fp_i + fn_i}{tp_i + fn_i + fp_i + tn_i}\right)/l \tag{2}$$

$$Precision = \left(\sum_{i=1}^{l} \frac{tp_i}{tp_i + fp_i}\right)/l \tag{3}$$

$$Recall = \left(\sum_{i=1}^{l} \frac{tp_i}{tp_i + fn_i}\right)/l \tag{4}$$

$$Fscore = \sum_{i=1}^{l} \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{5}$$

where tp_i is the number true positive class, tn_i is the number true negative class, fp_i is the number false positive class, fn_i is the number false negative class, l is the number of evaluated class.

The k-fold cross-validation technique divides the dataset into k equally sized segments, or folds [32]. For each of the k iterations, the model is trained and tested, with a different fold being used as the validation set each time, and the remaining folds comprising the training set.

This approach guarantees that every data point is used for both training and validation at least once, thereby reducing the likelihood of evaluation bias. In each cycle, the model is trained on a specific subset and validated on a distinct one. The overall performance of the model is then determined by averaging the outcomes from all k iterations (Figure 4). In this research, a 10-fold cross-validation was implemented [33]. Following the cross-validation, around 20% of the entire image collection, which included test data (100 images for each level of burn severity), was chosen at random for the final evaluation.

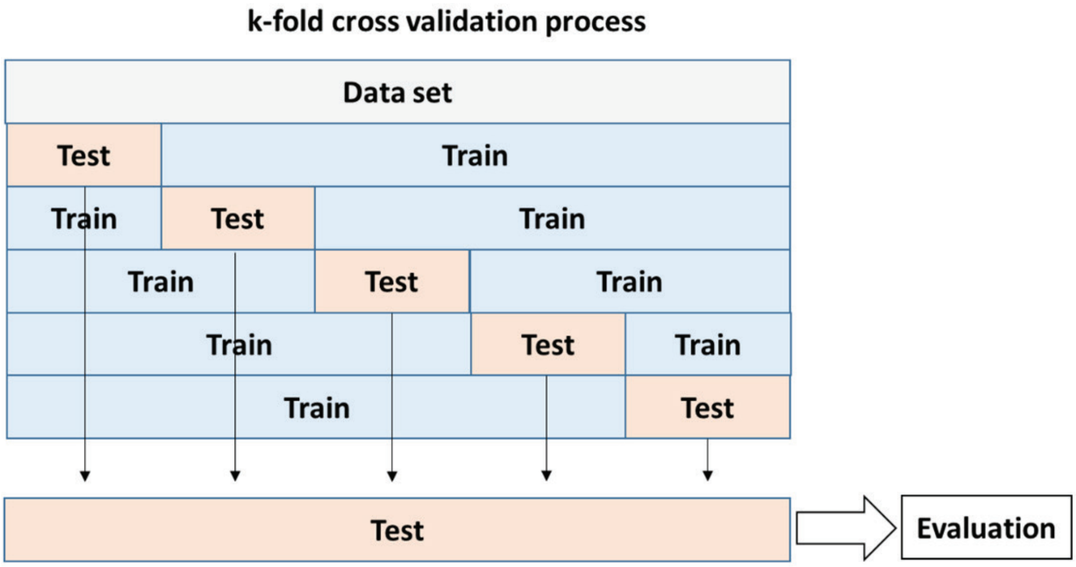

Figure 4. The schematic illustration of validation method of k-fold validation.

RESULTS AND DISCUSSION

In this study, the process of training burn injury images was conducted using three prominent deep learning architectures: GoogleNet, ResNet-50, and Inception-v3. These models, comprising 22, 50, and 48 layers respectively, were implemented within the MATLAB software environment to facilitate the training and evaluation process. The dataset utilized for training consisted of a total of 1,294 burn images, which were categorized according to burn severity. Specifically, the dataset included 561 first-degree burn images, 275 second-degree burn images, and 458 third-degree burn images. This distribution ensured that the models were exposed to a balanced variety of burn injury severities during the training phase.

To assess the performance of these deep learning models, the confusion matrix was employed as an evaluation tool. In the field of machine learning, particularly in statistical classification tasks, the confusion matrix serves as a valuable visual representation that illustrates the effectiveness of a classification algorithm, especially in supervised learning scenarios. This matrix is organized along two primary axes: the "actual" axis, representing the true class labels, and the "predicted" axis, denoting the classes

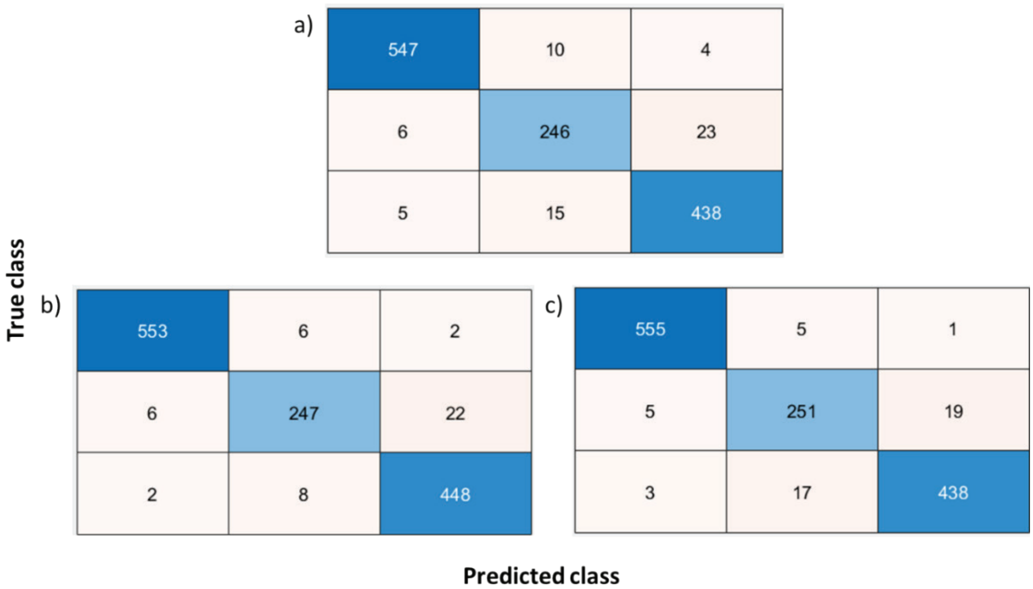

Figure 5. Confusion matrix for training process of a) GoogleNet, b) ResNet-50, and c) Inception-v3.

Table 1. Statistical evaluation for the training process

Network	Average accuracy	Error rate	Precision	Recall	Fscore
GoogleNet	96.75	3.25	94.33	94.20	94.26
ResNet-50	97.63	2.37	96.04	95.40	95.72
Inception-v3	97.42	2.58	95.38	95.28	95.33

predicted by the model. Rows correspond to the true labels, while columns indicate the predicted labels. In this study, the confusion matrix was crucial for evaluating the predictive accuracy of the trained models: GoogleNet, ResNet-50, and Inception-v3. As depicted in Figure 5, the matrix employs blue markers to signify correctly classified samples, while other colors are used to represent misclassified instances for each burn class category. During the training phase, the performance of each model varied in terms of misclassification rates. The GoogleNet model was found to have 63 misclassifications out of the total 1,294 samples. In comparison, the ResNet-50 model achieved a lower misclassification count of 46, while the Inception-v3 model recorded 50 misclassified samples. These results indicate that ResNet-50 and Inception-v3 outperformed GoogleNet in terms of predictive accuracy during the training phase. Consequently, the reduced error rates observed in ResNet-50 and Inception-v3 suggest that these two models demonstrated greater effectiveness in learning and distinguishing the visual features associated with burn injury severity.

Table 1 outlines the statistical metrics used for evaluation in this study, including average accuracy, error rate, precision, recall, and F-score. The data show that GoogleNet, ResNet-50, and Inception-v3 achieved average accuracies of 96.75%, 97.63%, and 97.42%, respectively. These results highlight ResNet-50's superior efficacy in the training phase over GoogleNet and Inception-v3. Further analysis of additional statistical measures such as error rate, precision, recall, and F-score reinforces the finding that ResNet-50 surpasses GoogleNet and Inception-v3 in both precision and training efficiency.

Khan et al. [21] aimed to categorize wounds into 1st, 2nd, and 3rd-degree burns through Deep Convolutional Neural Network (DCNN) approaches, achieving a reported accuracy of 79.4%. Chauhan and Goyal [22] developed a DCNN model to evaluate burn severity across different body regions, including the face, hand, back, and inner forearm, employing ResNet50, VGG16, and VGG19 networks, which yielded accuracies of 83.5%, 72.0%, and 70.7%, respectively. In a subsequent study, Chauhan and Goyal [23] applied a deep learning technique using the ResNet-101 model for the intricate task of segmenting burn regions. Additionally, Suha and Sanam [24] explored various classification models such as Logistic Regression, K-Nearest Neighbor, Support Vector Machine, Decision Tree, Random Forest, and Multilayer Perceptron to classify burns into three degrees of severity, noting the highest accuracy of 80% achieved by the Random Forest classifier. These findings underscore the superior predictive performance of the networks utilized in this study compared to those reported in existing literature.

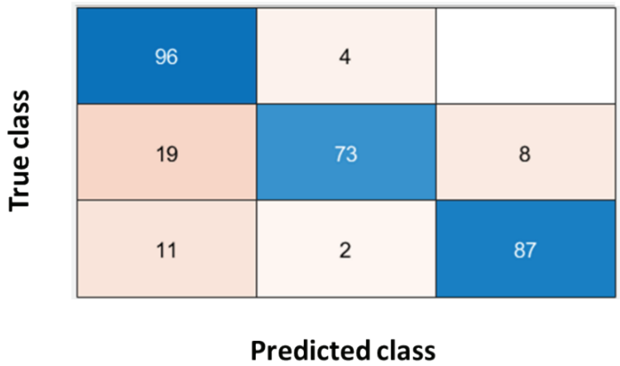

Figure 6. Confusion matrix for validation process of ResNet-50.

For evaluating the validation performance of ResNet-50, we constructed a confusion matrix, shown in Figure 6. In this visualization, blue markers signify accurate predictions, whereas various other colors represent the frequency of errors across distinct classes. Out of 300 tested burn images, ResNet-50 was responsible for 44 inaccuracies. These outcomes indicate that Inception-v3 achieved the greatest precision in identifying the severity of burns, surpassing the accuracy levels of both GoogleNet and ResNet-50.

Table 2 summarizes the statistical metrics used for evaluation, including average accuracy, error rate, precision, recall, and F-score. In the validation phase, ResNet-50 achieved an average accuracy rate of 90.22% and an error

Table 2. Statistical evaluation for the validation process

Network	Average accuracy	Error rate	Precision	Recall	Fscore
ResNet-50	90.22	9.78	86.72	85.33	86.02

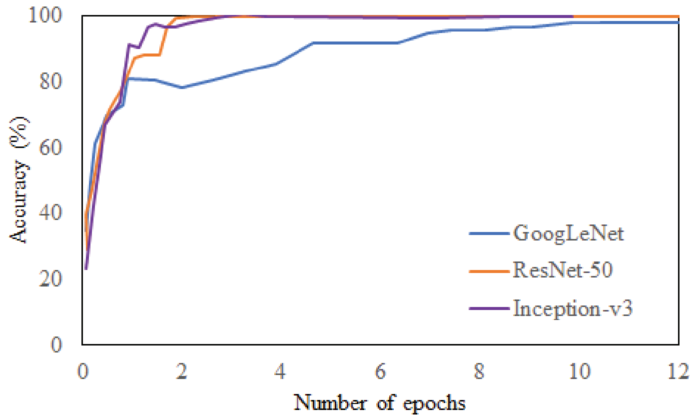

Figure 7. Accuracy of the deep learning algorithms for training process by iteration.

rate of 9.78%. The metrics for precision, recall, and F-score were recorded at 86.72, 85.33, and 86.02, respectively. These results demonstrate that ResNet-50 exhibited notable predictive performance in assessing the severity of burns during the validation stage.

The outcomes from the training and validation phases, including confusion matrices and statistical metrics, have consistently shown that ResNet-50 surpasses other deep convolutional neural networks in performance. It is important to note that the time required to train these deep learning models can differ based on the computing setup. For instance, on a system with an Intel(R) Core(TM) i5-1035G1 CPU @ 1.00GHz 1.19GHz, the initial 10 training iterations took 18 minutes for GoogleNet, 27 minutes for ResNet-50, and 22 minutes for Inception-v3. This suggests that GoogleNet was the most time-efficient model for training (as shown in Figure 7).

The file sizes of GoogleNet, ResNet-50, and Inception-v3 within Matlab's deep learning toolbox are 27.0 MB, 96 MB, and 89 MB, respectively. This variation in size reflects the different levels of complexity and the scale of the networks, indicating that GoogleNet may offer benefits in training speed for less complex classification tasks. However, when evaluating the total time needed to train all images in this research, GoogleNet, ResNet-50, and Inception-v3 took 160 minutes, 312 minutes, and 258 minutes, respectively. These findings suggest that ResNet-50 stands out as the preferred deep learning algorithm, balancing both high accuracy and efficient processing capabilities.

CONCLUSION

This research presents a novel approach using a Deep Convolutional Neural Network (DCNN) model designed to accurately identify and classify the severity of skin burns based on images sourced from medical atlases and textbooks. The model utilizes these images to extract critical features, which are then processed through a fully connected feedforward neural network. This network is tasked with categorizing the burns into three distinct severity levels: first-degree, second-degree, and third-degree burns. The DCNN model introduced in this study is poised to significantly aid medical practitioners and healthcare providers by offering a swift and reliable tool for assessing the severity of skin burns, thereby facilitating timely and appropriate treatment decisions. The application of this DCNN-based model extends beyond conventional clinical settings. This approach holds significant promise for enhancing telemedicine efforts, particularly in remote rural areas or developing countries where medical professionals are notably scarce. This technology is particularly beneficial in healthcare settings that are constrained by resources, enabling these facilities to conduct clinical diagnoses of burn severity with greater efficiency and accuracy. Utilizing deep learning to evaluate burn severity, this innovation is set to enhance the treatment process by providing healthcare professionals with a fast, unbiased, and accurate tool for assessing burns. Such deep learning-based assessment interfaces are capable of processing extensive datasets to ensure the rapid categorization of burn injuries, thereby streamlining patient management. These digital platforms not only support healthcare workers through educational resources and guidance but also facilitate the gathering and analysis of data for epidemiological research and enable remote consultations and assessments. This technology's influence on the management of burn injuries, a significant public health challenge, is considerable. It aids in efforts towards burn prevention and boosts the efficacy of treatment approaches, ultimately leading to better patient outcomes. Future expansions of this study could include the incorporation of real patient images to refine the model's ability to differentiate between superficial-partial and deep-partial thickness burns, along with algorithms to estimate the Total Body Surface Area (TBSA%) affected. This enhancement would provide a more comprehensive clinical tool for the assessment and management of burn patients, further contributing to the advancement of patient care and treatment methodologies.

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AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

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