Detection Burns of Skin Using Deep Learning Algorithms

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Abstract. An application to determine the cause of the burn, its depth and degree, and the percentage of fluids lost from the body is calculated with a parkland equation to replace it with fluids. Burn wounds have always been one of the world's most common injury, ranging from first-degree, where the burn will only affect the epidermal layer (the outermost layer) of the skin, to the third-degree, where the burn would (at minimum) extends to the fat layer(beneath the dermal layer) of the skin, and may have several dangerous effects to the wounded individual, dangerous enough to the point that the burned part of the body would sometimes be required to be grafted in order to fully close the burn wound and prevent any further infection or any further negative aftereffects .

1. Introduction

Burn wounds has always been one of the world's most common injury, ranging from first degree, where the burn will only affect the epidermal layer (the outermost layer) of the skin, to the third degree, where the burn would (at minimum) extends to the fat layer (beneath the dermal layer) of the skin, and may have several dangerous effects to the wounded individual, dangerous enough to the point that the burned part of the body would sometimes be required to be grafted in order to fully close the burn wound and prevent any further infection or any further negative aftereffects.

The most prevalent problem in the subject of burn wound degree is the comparison between second-degree burn and third-degree burn, as there are some cases where the difference would be minimal, and people, including the wounded individual, would sometimes think lightly of a burn wound that they thought was a second-degree burn when, in reality, it was a third-degree burn. Cases as such this often happen around the world, with people having to deal with the aftereffects only after quite some time has passed, cases such as a light third-degree burn, which should've been able to be dealt with using several antibiotics and other medicines to improve the natural recovery rate of the burnt part of the skin, was left alone for too long and using Resnet model the ResNet model's resilience to deep network challenges, its effectiveness in feature extraction from images, and its proven track record in image classification tasks make it a powerful tool for classifying burn injuries based on skin images. Its application in the

Parkland formula, also known as the Parkland-Baxter formula, is a medical formula used to estimate fluid resuscitation requirements in burn patients during the initial 24 hours after injury. It is named after the Parkland Memorial Hospital in Dallas, Texas, where it was developed.

The formula is used to calculate the total volume of fluid (usually in milliliters) that should be administered within the first 24 hours post-burn. The formula is as follows:

Fluid volume (in mL) =4 mL×total body surface area (TBSA) of the burn×body weight (in kg)

Fluid volume = 4 mL * 30 * 70

Fluid volume = 4 mL * 2100

Fluid volume = 8400 mL

Here's how it works:

1. **Total Body Surface Area (TBSA) of the Burn:** This is estimated as a percentage of the total body surface area affected by burns. Various methods can be used to estimate TBSA, such as the Rule of Nines or the Lund and Browder chart, which take into account the different proportions of body surface area affected by burns in adults and children.
2. **Body Weight:** This is the weight of the patient in kilograms (kg).
3. **Fluid Volume:** The result of the calculation gives the total volume of fluid (typically a balanced electrolyte solution such as lactated Ringer's

solution) that should be administered over the first 24 hours after the burn injury.

Example Calculation:

Let's say a patient has a burn affecting 30% of their TBSA and weighs 70 kg.

It's important to note that the fluid resuscitation should be administered carefully and adjusted based on the patient's response, urine output, and clinical status. This formula provides a starting point for fluid management in burn patients and is a critical part of initial burn care protocols to prevent hypovolemic shock and maintain organ perfusion.

medical imaging, including burn severity assessment, showcases its potential to enhance diagnostic accuracy and improve patient care outcomes.

2. Methodology

2.1 Dataset

The data contains images of the degrees of burns, as it contains 43983 images divided into 18010 images for the first degree, 16927 images for the second degree, and 9046 for the third degree. The data is divided into training, testing and validation, divided into 80% for training, 10% for testing and 10% for validation as shown in the next table.

Table 1. Total of images for each class

	First burn degree	Second burn degree	Third burn degree
Train	14,408	13.541	7200
Valid	1,801	1,693	923
Test	1,801	1,693	923
Total	18,010	16,927	9,046

2.2 Background

The detection of skin burns using deep learning algorithms, particularly ResNet-50, [5] represents an innovative application of AI in healthcare. Deep learning, a subset of machine learning, involves training multi-layered neural networks to recognize patterns in large datasets. ResNet-50, introduced by Microsoft researchers in 2015, is a 50-layer deep convolutional neural network designed to overcome the vanishing gradient problem through the use of residual blocks. These blocks include shortcut connections that allow gradients to flow more easily through the network, enhancing training efficiency and accuracy.

ResNet-50's depth enables it to capture a wide range of features, from low-level textures to high-level patterns, making it highly effective for image classification tasks. When applied to burn detection, ResNet-50 is trained on a labeled dataset of medical images depicting various types and severities of burn injuries. This training allows the model to identify and classify burns accurately, which is crucial for timely and precise medical diagnostics. The automated analysis provided by ResNet-50 ensures consistent and objective evaluations, reducing human error and improving patient outcomes. Additionally, the model's efficiency supports rapid processing and decision-making in emergency scenarios.

Artificial Intelligence and Machine Learning: Artificial Intelligence (AI) [1] aims to create systems that perform tasks requiring human intelligence, such as virtual assistants and search predictions. Machine learning (ML), [2] a branch of AI, automates analytical model building, allowing systems to learn from data, identify patterns, and make decisions with minimal human intervention. Key ML algorithms include linear regression, logistic regression, Naive Bayes, and K-means clustering.

Computer Vision: Computer vision, [3] a field within AI, enables computers to extract meaningful information from images and videos. Techniques such as image classification, object detection, and semantic segmentation allow computers to recognize and interpret visual data. Image classification [4] predicts the class of an image, while object detection [5] identifies and locates objects within an image. Semantic [6] and instance [7] segmentation assign labels to every pixel in an image, distinguishing different objects and instances within the same category.

Deep Learning: Deep learning,[8] a subset of ML, uses deep neural networks to mimic the human brain's ability to learn. It is essential for processing large amounts of complex data and achieving state-of-the-art accuracy in tasks such as image recognition. Common deep learning algorithms include Convolutional Neural Networks (CNNs), Artificial Neural Networks (ANNs), and Long Short-Term Memory Networks (LSTMs).

ResNet-50 for Burn Detection [5]: ResNet-50 is chosen for burn detection due to its high accuracy, residual learning capabilities, depth, and transfer learning capabilities. It is efficient and fast, making it suitable for real-time applications. The model has proven successful in various medical imaging tasks, handling complex input data variations effectively. The architecture of ResNet-50 includes convolutional layers, batch normalization, ReLU activation functions, and fully connected layers, making it robust and scalable for improving burn care quality and efficiency.

Implementation of ResNet-50 for Burn Detection

•Data Collection and Annotation: Assemble a diverse dataset of annotated skin burn images.

•Set Up ResNet-50: Download the ResNet-50 model and configure it for your dataset.

•Data Preprocessing and Training: Prepare the dataset, train the model, and fine-tune for optimal performance.

•Model Evaluation and Validation: Evaluate and optimize the model using a validation dataset.

•Convert Model to TensorFlow Lite: Convert the trained model for deployment in a mobile app.

•Integration with Flutter: Choose a TensorFlow Lite plugin for Flutter and integrate the model into your app.

•App Development: Design the user interface, implement image capture, perform inference, and display results.

•Skin Burn Analysis: Calculate fluid loss percentages and allow user interactions for detailed analysis.

•Testing and Deployment: Test the app, ensure security and privacy standards, and publish on app stores.

This comprehensive approach ensures that the ResNet-50 model for burn detection is accurate, efficient, and ready for practical use in medical settings.

3. previous work

In 2023 Julius Ferdinand1, Davy Variya Chow2, and Simeon Yuda Pra-setyo3[12]

In this study, an automated system for skin burns detection and severity classification using YOLO Convolutional Neural Network (CNN) models was explored. The objective was to enhance paramedics' ability to administer appropriate treatment based on the severity of burns. The research utilized a diverse dataset from Kaggle and Roboflow, incorporating first, second, and third-degree burn images. Employing YOLOv5l, the best-performing model achieved an F1-Score of 75.9% and a Map of 83.1% after hyperparameter tuning. This indicates the model's accuracy in detecting and classifying skin burn severity. Advantages include automated detection and severity classification, leveraging a substantial dataset. However, limitations include potential dataset constraints and reliance on specific evaluation metrics, suggesting the need for cautious interpretation of the model's overall performance and generalizability to real-world scenarios.

Advantages:
1. Automated skin burn detection: The use of YOLO CNN models enables auto-mated detection of skin burns, which can assist in timely medical intervention.
2. Severity classification: The models can classify the severity of burns, aiding paramedics in providing appropriate treatment.
3. Dataset availability: The study utilized a dataset gathered from Kaggle and Roboflow, providing a substantial collection of labeled burn images for training and evaluation.

Disadvantages:
1. Dataset limitations: Although the study used a dataset from Kaggle and Roboflow, the dataset may still have limitations in terms of diversity and representativeness.

2. Evaluation metrics: The study primarily used F1-Score and Map as evaluation metrics, which may not capture all aspects of model performance or generalizability to real-world scenarios.

Result and Accuracy:
The best-performing model, YOLOv5l, achieved an F1-Score of 75.9% and a mAP of 83.1% after hyperparameter tuning. These metrics indicate the model's accuracy in detecting and classifying skin burn severity. However, it's important to note that the overall accuracy and generalizability of the model may depend on various factors, such as the dataset used and the specific conditions in real-life applications.

In 2016 Indian Journal of Science and Technology Hai Son Tran1, Thai Hoang Le2 and Thuy ThanhNguyen3 [9]

In this study on skin burn detection, the proposed method utilizes convolutional neural networks (CNN) and augmentation techniques for efficient feature extraction, aiming to diagnose burns promptly and accurately. The model achieves commendable results with 94% accuracy in the training set and 92% in the testing set. By focusing on classifying burns based on the degree of injury using skin grafting techniques, the model categorizes burns into superficial, deep, and full thickness, emphasizing color and local shape for classification. Despite the limited dataset of 90 images, the proposed CNN-based model out-performs SVM algorithms, showcasing its potential for improved burn detection. However, the study lacks detailed information on methodology and comparisons with existing methods, limiting a comprehensive evaluation of its performance.

Disadvantages:

1. Limited Dataset: The paper uses only a small number of pictures of skin burns from one hospital. It might miss out on different types of burns from other places.

2. Lack of Comparison: The paper doesn't check how well its model works com-pared to other ways of recognizing skin burns. It's hard to know if it's better or worse than other methods.

3. Real-World Testing Missing: The paper doesn't talk much about how well the model works in real hospitals with different patients. It's mostly based on the pictures it was trained on.

Results and Accuracy
The proposed Burn Convolutional Neural Network (B-CNN) model achieved an accuracy rate of 92.5% in classifying skin burn images into four degrees. The experimental results demonstrated the model's feasibility and accuracy, indicating its potential as a computer-aided tool for classifying burn degrees and aiding medical decisions in remote hospitals in Vietnam.

In 2022 Noor M. Abdulhadi, Noor A. Ibraheem, and Mokhtar M. Hasan [13]

The paper introduces a burning skin detection system using an unsupervised deep learning algorithm to accurately detect and classify burn areas in medical images. The proposed system achieves system accuracy of 75%, outperforming state-of-the-art techniques. The main advantage of the system is its simplicity and suitability for real-life applications. However, the current diagnostic approach for burn depth still relies on subjective assessments by clinicians, indicating a limitation. Overall, the integration of deep learning algorithms with im-age analysis technology shows promising potential for improving burn depth diagnosis and prognosis in clinical settings.

Advantages:
1. Objective and Consistent Results: By leveraging deep learning algorithms, the system aims to provide objective and consistent results in detecting and classifying burn areas in medical images. This reduces the subjectivity associated with human judgment and increases reliability.

2. Potential Time and Cost Savings: Automating the burn depth diagnosis process through the proposed system can potentially save time for clinicians, as well as reduce the need for extensive manual analysis and interpretation of medical images. This could lead to cost savings in healthcare settings.

3. Extensibility and Adaptability: Deep learning algorithms have the advantage of being able to learn from large amounts of data and adapt to various scenarios. The system's ability to integrate with different medical imaging technologies and adapt to new datasets makes it potentially applicable in diverse healthcare settings.

Disadvantages:

1. Dependency on High-Quality Data: Deep learning algorithms heavily rely on the quality, size, and diversity of the training dataset. If the dataset used to train the system is limited, biased, or not representative of the target population, it may affect the system's performance and generalizability.

2. Interpretability Challenges: Deep learning algorithms are often considered black-box models, meaning they provide accurate predictions but lack interpretability. Understanding the reasoning behind the system's decisions may be challenging, especially in a medical context where interpretability is crucial.
2 Ethical Considerations: Implementing AI systems in healthcare requires ad-dressing ethical concerns such as data privacy, security, and

potential biases. The research paper does not specifically address these ethical considerations.

Results and Accuracy:

According to the research paper, the proposed burning skin detection system achieved an accuracy of 75% when compared to some state-of-the-art techniques. However, it's important to note that the specific evaluation metrics, such as precision, recall, or F1 score, are not mentioned in the abstract or avail-able information. The accuracy of 75% indicates that the system has room for improvement and may not be fully reliable for critical decisions without further refinement and validation.
In summary, while the proposed burning skin detection system shows promise in improving burn depth diagnosis, its performance and applicability may be influenced by factors such as data quality, interpretability challenges, and ethical considerations. Further research and validation are necessary to address these limitations and ensure the system's effectiveness in real-world clinical settings.

In 2021 ashishs. sharma in India [14]

In this study on skin burn detection, the proposed method utilizes convolutional neural networks (CNN) and augmentation techniques for efficient feature extraction, aiming to diagnose burns promptly and accurately. The model achieves commendable results with 94% accuracy in the training set and 92% in the testing set. By focusing on classifying burns based on the degree of injury using skin grafting techniques, the model categorizes burns into superficial, deep, and full thickness, emphasizing color and local shape for classification. Despite the limited dataset of 90 images, the proposed CNN-based model out-performs SVM algorithms, showcasing its potential for improved burn detection. However, the study lacks detailed information on methodology and comparisons with existing methods, limiting a comprehensive evaluation of its performance.

Advantages:

1. Fast diagnosis: The proposed method aims to provide fast detection of burn areas and assess the impact on the body, enabling timely medical treatment.

2. Improved accuracy: By using CNN and augmentation techniques, the model achieves high accuracy rates of 94% in the training set and 92% in the testing set.

3. Extension of CNN model: The paper presents an extension of the CNN model using augmentation to improve the outcome, indicating the potential for further enhancing burn detection methods

Disadvantages:

1. Limited dataset: The BIS dataset used for training contains only 90 images, which may limit the generalization and performance evaluation of the proposed approach. More diverse and larger datasets would be beneficial for robust model training.

2. Lack of comparison: The paper does not provide a direct comparison with existing burn detection methods or alternative approaches, making it difficult to assess the superiority of the proposed model in relation to other techniques.

3. Limited information: The truncated content does not provide detailed information about the specific feature extraction methods, CNN architecture, augmentation techniques, or evaluation metrics used in the study. This limits a comprehensive understanding of the methodology.

Result and Accuracy:

The proposed model achieves a training set accuracy of 94% and a testing set accuracy of 92%. These results indicate that the model performs well in identifying burn areas and assessing the impact of burns on the body. However, with-out further details or comparison with other methods, it is challenging to assess the model's performance in relation to existing approaches accurately.
Three algorithms were used in the study. The first one is the MLSF-SVM algorithm, which achieved an accuracy of 84.12%. The second algorithm is the EMS-SVM, which achieved an accuracy of 92%. The third algorithm, which performed the best, is the Augmented CNN Based Model for Burn, with an accuracy of 94%.

In 2021 Rohan Bhansali and Rahul Kumar in Loudoun [15]

An Efficient Deep Learning Framework for Accurate Dermal Burn Classification" discusses the development of an eight-layer convolutional neural network called BurnNet for the accurate classification of dermal burns. The authors highlight the importance of accurate burn diagnosis for effective treatment and surgical intervention. They point out that current diagnosis methods by burn surgeons and dermatologists have an accuracy rate of approximately 50-75%.
To address this issue, they used BurnNet, which achieved a classification accuracy of 99.87% in their experiments.

Advantage:

1. High Classification Accuracy: BurnNet achieved a classification accuracy of 99.87% in the experiments conducted by the authors. This high accuracy demonstrates the potential of deep learning frameworks like BurnNet in accurately classifying dermal burns, which can aid in effective treatment decisions.

2.Automation and Efficiency: BurnNet's development and deployment as an automated deep learning framework can potentially streamline the burn classification process. This automation can save time for medical professionals and reduce the subjectivity associated with manual diagnoses.

3.Potential for Improved Diagnosis: BurnNet outperformed trained professionals in dermal burn classification. By leveraging deep learning algorithms, Burn-Net has the potential to enhance diagnostic accuracy and improve patient out-comes.

4. Scalability: Deep learning frameworks like BurnNet can be scaled to handle large volumes of burn images. This scalability allows for the analysis of vast datasets, which could lead to the discovery of patterns and insights that may not be easily discernible with traditional manual methods.

Disadvantage:

1. Limited Generalization: The performance of BurnNet was evaluated on a specific dataset, namely the BIP_US database. The generalization of BurnNet to other datasets or real-world scenarios is not explicitly discussed in the article. It is important to validate the model's performance on diverse datasets to ensure its effectiveness across different populations and burn types.

2. Interpretability: Deep learning models like BurnNet are often considered "black boxes" because

it can be challenging to understand how they arrive at their decisions. Interpretability is crucial in medical applications, where clinicians need to understand the rationale behind a model's predictions. Ensuring interpretability and transparency in BurnNet's decision-making process is an important consideration.

3. Data Requirements: Deep learning models, including BurnNet, typically re-quire large amounts of labeled training data to achieve high performance. Collecting and annotating such datasets can be time-consuming, costly, and labor-intensive. Additionally, the availability of diverse and representative datasets can influence the model's ability to generalize to different burn types and demographics.

What will we add?
We will calculate the fluids lost by the body when burned using several equations**:**

Among these equations
Parkland:

The **Parkland formula**. This formula is used for resuscitation of burns >10% total body surface area (TBSA) in children and the elderly, and for burns >20% TBSA in adults.

The Parkland formula consists of 4 mL/kg per %TBSA burn of lactated Ringer's (LR) for the first 24 hours. Colloid and D5½NS maintenance fluid is given beginning at 24 hours post-burn as described below:

2 mL/kg per %TBSA given over first 8 hours post-burn.

1 mL/kg per %TBSA given over second 8 hours post-burn.

1 mL/kg per %TBSA given over third 8 hours post-burn.

0.1 mL/kg per %TBSA of 25% albumin given over the first 4 hours of the second day.

1 mL/kg per %TBSA D5½NS given per day of maintenance fluid.

The Parkland formula is used only as a guide for resuscitation. The patient is continually reassessed with frequent vital signs. A Foley catheter is mandatory, as urine output is the single best indicator of adequacy of resuscitation. The resuscitation is adjusted to keep a urine output between 0.5 and 1 mL/kg per hour (30 to50 mL/hour in adults).

Peripheral intravenous access is preferable and adequate during the resuscitation of the majority of burn patients. Catheters are sutured in place.
Central venous pressure monitoring and pulmonary artery catheterization are not routinely used and are reserved for patients who do not appropriately respond to resuscitation or who have known compromised cardiac function.

Salt-poor albumin solution (25% solution) is administered beginning 24 hours post-burn (after the burn induced capillary leak has resolved).

Maintenance fluids are replaced with D5½NS.

Packed red blood cells are transfused only in anemic patients.

The patient is given both active and passive tetanus prophylaxis in the contralateral deltoid muscles while in the emergency department. The dose of tetanus immune globulin (Hypertet) is 4 units/kg and is the only medication that should be administered intramuscularly to the burn patient as these patients have poor skin and muscle perfusion acutely.

A nasogastric tube is inserted to prevent gastric dilation, vomiting, and aspiration with burns >25% TBSA because burn patients have a tendency to develop an ileus. It is also used for early initiation of enteral feeding.

H2 blockers are used intravenously to prevent gastric stress ulceration.

Prophylactic antibiotics are not administered unless there is an indication from a concomitant injury such as an open fracture or a preexisting comorbidity such as a mechanical valve replacement.

All adults receive subcutaneous heparin for deep venous thrombosis prophylaxis

4. Result and Accuracy:

The classification report for burn degree prediction exhibits a high level of performance across various metrics. For 1st degree burns, the model achieved a precision of 0.96, a recall of 0.87, and an F1-score of 0.91 based on 1801 cases. In the case of 2nd degree burns, the precision was slightly lower at 0.81, but the recall was higher at 0.93, leading to an F1-score of 0.87 from 1693 instances. For 3rd degree burns, the model demonstrated a precision of 0.93, a recall of 0.86, and an F1-score of 0.89, evaluated on 923 cases. Overall, the model's accuracy stands at 0.89 across all 4417 instances. The macro average metrics, which provide an average of the individual classes' metrics, showed a precision of 0.90, a recall of 0.88, and an F1-score of 0.89. Similarly, the weighted averages, which account for the support of each class, yielded a precision of 0.90, a recall of 0.89, and an F1-score of 0.89. These results indicate a robust performance of the model in classifying different degrees of burns.

The image is a line plot showing the loss of the model during training and validation epochs as illustrate in next figure.

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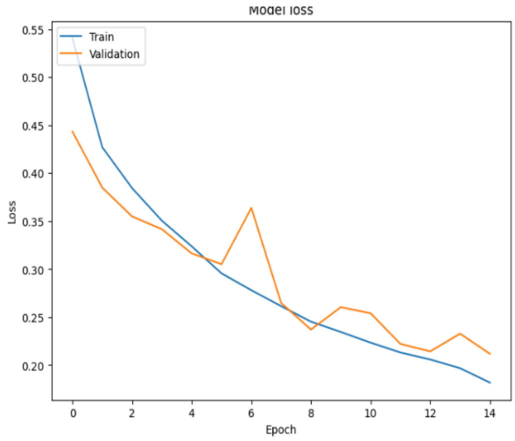

Fig 1. Training And Validation Loss

The image is a line plot showing the accuracy of the model during training and validation epochs as illustrated in next figure.

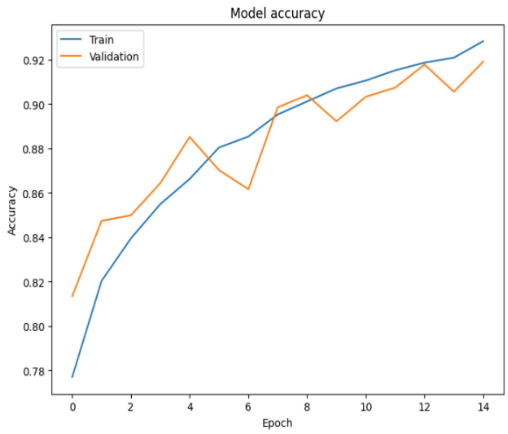

Fig 2. Training And Validation Accuracy

5. Conclusion

In conclusion our project has successfully developed a robust and efficient system for detect the degree of burn using deep learning, we have implemented a various components and technologies to ensure accurate detection.

We use ResNet's as the deep learning model, ResNet's main advantage lies in its ability to facilitate the training of very deep networks through skip connections, which mitigate the vanishing gradient problem. Its architecture is more straightforward and often more computationally efficient than DenseNet.

The integration of the model with flutter-based website using an API allowing the users to upload the image and receive back the degree of the burn as 1st,2nd and 3rd degree and the Percentage of lost fluids.

Throughout the development process, we prioritized functional and non-functional requirements to meet the needs of users and system performance. We applying Extensive testing, including unit testing and integration testing to ensure the system's reliability, accuracy and functionality. Performance optimization techniques, such as algorithmic efficiency. Caching and parallel processing were implemented to enhance the system's speed and responsiveness.pg. 100

The results and discussions chapter showcased the effectiveness of the system in accurately analyzing lung diseases. Through comprehensive testing and evaluation, we observed high accuracy rates in burn degree detection and reliable analysis results

In summary our project has successfully developed an effective and user-friendly system for burn detection using deep learning between 3 degrees of burn. The project has demonstrated the feasibility and potential of integrating advanced technologies to improve the accuracy and efficiency of burn image detection with accuracy 90%

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