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Deep Learning Model for Burn Injury Assessment with Enhanced Diagnosis Rate

C. Pabitha[1], K. Revathi[2*], R. Krishna Priya[3]

[1]Department of Computer Science and Engineering, SRM Valliammai Engineering College, SRM Nagar, Kattankulathur, Chennai 603203, Tamil Nadu, India.

[2]Department of Information Technology, SRM Valliammai Engineering College, SRM Nagar, Kattankulathur, Chennai 603203, Tamil Nadu, India.

[3]Department of Artificial Intelligence and Data Science, Sri Sai Ram Institute of Technology, Sai Leo Nagar, West Tambaram, Chennai 600044, Tamil Nadu, India.

corresponding author: (revathik.it@srmvalliammai.ac.in; ORCiD: 0000-0003-3411-9264)

Abstract - The skin is considered as the largest organ of our body specifically satisfies the environment. As a result, the skin is vulnerable to various injuries, especially burns. Burns are linked to high rates of morbidity and mortality and can be fatal. Effective diagnosis supported by precise evaluation of the burn area and the depth of wound is critical for enabling efficacy in clinical settings. The characteristics of a burn wound on the skin include: the wound is abnormal, the skin is infected, there is discomfort, the skin is tight, and there are raised areas of skin. To properly diagnose burn injuries a genomic analysis for skin tissue is necessary. In existing studies, various machine learning algorithms exercised over vast datasets to identify the wound patterns and classify the same accordingly. The multilayered neural network used in the deep learning is renowned as a subset of machine learning and resembles the architecture of human neural circuits. Automatically extracting features from a burn image and classifying the wound based on severity is possible with deep neural networks. Our method involves using deep learning techniques to analyse the genome in skin burn wounds according to the extent of damage. Our goal is to examine various deep learning approaches that can support skin genomic analysis and to improve the diagnostic rate of burn injury with the help of tissue segmentation. Further the scope for repairing the tissue which enables quick advancements in skin care is discussed. The development of deep learning techniques has opened a significant avenue for medical image processing and burn trauma cases.

Keywords— Skin Genome, Tissue Segmentation, Deep Learning, Skin Burn, Predictive Diagnosis.

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1. INTRODUCTION

As with all other forms of damage, a burn is the most psychologically and physically challenging injury, and its consequences are widespread: it impacts on nearly every organ system and the skin, which is the body's outermost organ. It also causes significant morbidity and death, making it one of the most problematic conditions. The largest

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organ in the body and the one that is most exposed to the outside world is skin. As a result, the skin is vulnerable to burns and other forms of injury. Skin wounds heal more slowly and with greater severity. It starts early in the burn wound and sets off a chain of systemic and local reactions that affect tissue and cell survival and, in turn, wound healing and recovery.

With the use of several medical techniques, skin burn recovery success rates have dramatically increased. The location and depth of the burns are important determinants of their severity. Precisely determining the extent of the burn is essential for wound care and treatment planning. Grading delays raise the risk of infection and scarring because they cause delays in burn treatment. Based on the extent of the damage, machine learning offers several classification algorithms that reliably categorize burn wounds. Tissue regeneration is the process by which a portion of the body's tissue that has been damaged by outside factors and is partially gone grows back with the same structure and function as the lost portion. This repair process is known as tissue regeneration, and it involves the regeneration of blood vessels, muscle tissue, nerve cells, cartilage and bone tissue, fibrous tissue, epithelial tissue, and cartilage. Extreme scarring, deformity, and persistently tight and itchy skin are common side effects of extensive skin lesions. This is because, rather of growing or repairing healthy skin tissue, the body's healing mechanisms have developed to rapidly seal wounds to prevent infection.

Later, appropriate medical remedies are provided, which makes the problem much more difficult to solve. Automation has fascinated humans since the dawn of technology. Artificial Intelligence (AI) makes it possible for machines to think without human assistance. It is a wide area in computer science. Three categories of AI systems can be distinguished: Narrow Artificial Intelligence (ANI) is goal-oriented and configured to carry out a specific task. Artificial General Intelligence (AGI) enables machines to learn, comprehend, and behave in a setting that is indistinguishable from that of humans. In the hypothetical AI known as Artificial Super Intelligence (ASI), computers can exhibit intelligence that is superior to that of the most intelligent humans. Statistical learning algorithms are used in the machine learning models, a subdivision of AI, to build systems that can learn and enhance user experiences without the need for explicit programming. Voice assistants like Google Home and Amazon Alexa, Netflix, YouTube, and Spotify systems; and search engines like Google and Yahoo.

By supplying a lot of data and understanding more about the information being processed, we train the algorithm in machine learning. The way the human brain filters information served as the inspiration for the machine learning technology known as deep learning. In essence, it picks up knowledge from examples. It assists a computer model in classifying and predicting information by filtering the input data through layers. Deep learning is often utilized in applications that are typically performed by humans because it processes information similarly to how the human brain does. These developments in machine intelligence can effectively analyse the genome of the skin and direct us to take the right actions as tissue regenerate, eliminating permanent skin scarring.

2. LITERATURE REVIEW

Convolutional neural networks, or CNNs, are mostly utilized for image classification and segmentation applications. Numerous application areas, including image processing, handwriting recognition, face recognition, and illness diagnosis, classification, and detection [1], [2], have made extensive use of it [3]. The ability of CNN to recognize and gather several rich general distinguishing qualities at different levels is the primary reason for its use.

To categorize and determine if the human bodies, and more especially photographs pertaining to skin, are clear and healthy or burnt and shrivelled, a novel method was presented in a study conducted by multiple authors in [4]. The method involves pre-training the image's attributes into a CNN; because to a lack of datasets, multiple models were employed. The CNN performs pre-processing tasks, which include resizing the image to a standard fixed size, supporting the model in which it can be implemented, and removing noisy data from the images. The smaller training datasets also contained RGB-formatted images. The training data was primarily implemented using the ResNet model. The Support Vector Machine (SVM) classification algorithm is used to implement the retrieved features, and tenfold cross validation is used for training. This method offers up to 99% classification accuracy for burned photos.

Binary classification of skin burns photos using deep learning ideas applied in neural network features is another method suggested in [5]. The SVM classification algorithm is also used in this approach. The three novel CNN models were utilized in this method; two of them where CNN models which were pre-trained using the ImageNet dataset, enabling them to categorize more than 5000 things in the image. The final model has already been trained to recognize faces. Overall, the three pre-trained CNN models were used mostly for classification and feature extraction. When the models VGG16 and VGG19 are used, the performance results show an accuracy of over 98% and 97%, respectively, while 95% accuracy is attained when face recognition is used. Ultimately, the authors concluded that ImageNet models are primarily responsible for achieving high percentage accuracy, which can be linked to the models' primary function of learning and classifying a wide range of feature categories.

The method used in [6] mostly makes use of the fundamental deep neural network models that may be pre-trained using a small number of datasets. The study also makes use of a well-liked method for deep neural network feature extraction called transfer learning. To separate burn photos from common skin conditions and allergies, two previously trained residual network models were applied for extracting features. For picture classification, SVMs were employed and trained. ResNet models exhibit higher distinguishing patterns from the training datasets when compared to one another. As a result, SVMs achieved an accuracy of over 99%.

The same binary classification of skin burn photos and fine-tuning technique are used in another method suggested in [7] to determine a healthy body. Additional top layers were added to the already-trained ImageNet model. The deep inner level layers of the models were taken out and supplanted with new layers; all inner level layers were formerly pre-trained utilizing characteristics along with traits from the base layer of the ResNet model. 97% of skin burn photos are correctly recognized by the program, and it obtained 99% classification accuracy on photographs with varying skin tones.

Very few studies apply machine learning techniques when considering the depth of burn wound detection. A study conducted in [8] employs Deep Partial Thickness (DPT), Superficial Partial Thickness (SPT), and machine learning to classify first-degree burns. The model first extracts features, then segments the relevant Region of Interest (ROI), uses the Discrete Wavelet Transforms (DWT) to eliminate textural information, and uses Principal Component Analysis (PCA) to minimize the dimensionality features and speed up the process. The best classification accuracy was obtained using simple logistic regression, which showed a performance high of 73%.

An automated diagnostic procedure that can categorize the different types of burn injuries was another approach put out in [9]. Images of skin burns and common skin conditions were categorized utilizing this process. Because of the lack of datasets, the conducted study used two methods: one attempted to fine-tune the deep learning mechanism by altering its top layers, and the other that trains SVM by incorporating features that were mined during the pre-training of the deep neural network model. Three previously trained models were used in this method, and the outcomes were contrasted. Finally, with a ROC curve of 99% and an accuracy of over 99%, the training of machine learning algorithms SVMs using ResNet are regarded as the best classifier. Compared to the other approaches, a significant number of datasets are used in this process.

According to a study by [10], various machine learning techniques are employed to classify skin burn photos according to the depth of the damage. The objective here is to design an automated diagnostic approach that helps in identifying either the burned sore needs surgery or any other form of treatment. By identifying this timely on, the right care can be given, delays can be avoided, and the healing period and likelihood of scarring are reduced to a greater degree. To derive features for chroma, colour, hue, hog, skew and vascular, the training images go through sorting and pre-processing. This study also makes use of SVM, which has been trained to obtain an F1-score of 82%, recall of 85%, and precision of 88%.

Another technique described in [11] makes use of pictures of skin burn wounds from about 500 mummers and suggests a discriminatory way to classify the lesion according to its depth and severity. After that, the burned images are shrunk, compressed, and converted into lower-level pixels in a different colour space. Every class of burn wounds, including first, second, and third degree, had a collection of photos that varied from 100 to 200. The study obtained a 75% accuracy rate using a variety of ROI-based classification and segmentation algorithms.

3. RESEARCH METHODOLOGY

The study of an organism's whole genome, which includes aspects of genetics, is called genomics. Genomics is a field that integrates reconbimeant DNA, various DNA sequencing methods, and bioinformatics for the purpose of sequencing, organizing, and examining the form and functionality of complex sets of genomes. Deep learning developments have spurred new fields of study in computational biology and bioinformatics and given biomedical informatics an unprecedented boost. In several genomics’ tasks, deep learning models can provide higher accuracy than the previous art methods. Compared to deep learning, machine learning's primary drawback is its inability to effectively handle natural data in its unprocessed state. It has also been demonstrated that deep learning produces more accurate models that are effective at identifying patterns in high-dimensional data, which makes them applicable to machine learning. However, deep learning models necessitate training data, and when learning deep, the quantity of training data is more demanding and significantly impacts the trained model's prediction value.

The most common neural network methodology is Artificial Neural Network (ANN) which is based on the human brain, its neurons, and how they connect with each other [10]. An ANN consists of a group of fully connected nodes, or neurons, which attempt to model how brain synapses and fire or are inhibited by a given input. Like other architectures in DL, these can act as standalone modules of a deeper architecture, or being utilized for feature selection, and then for classification and dimensionality reduction.

The CNN is a deep neural network architecture most often used in the analysis of visual imagery. It was designed as an automatic network for the analysis of images to classify handwritten characters. CNNs are an extension of fully connected networks, where in each layer, every node or neuron of a given layer is (fully) connected to all or a subset of nodes of the next layer. They reinforce the multilayer perceptron approach. An ANN could also be said to consist of a set of connected, adjustable units, each capable of sending a signal to one or more other units.

Compared with ANNs, the architecture of CNNs has multiple layers and tiers of convolution units. Each of the units in a layer 'captures' with units in the immediate layer 'below' and computes some weighted proximity. The essence of such a 'deep architecture' is the attempt to tackle non-linear mappings with high magnitudes of input and output by computing and blending feature maps to 'infer as many relationships as possible' [12, 13]. For image datasets, CNN is by far the most dominant approach to feature extraction, selection and even reduction.

Another well-liked method is Recurrent Neural Networks (RNN), which always act similarly to CNN but also work with general feed forward neural networks (FNN) [14], in which the connections between several nodes create a directed graph according to a temporal sequence [15]. This enables RNNs to integrate internal memory and display temporal dynamic behaviour. Recurrent networks may retain data from previously examined states thanks to this STM, which is ideal for prediction models and sequential signal processing. The ability of RNNs' idea models to relate data from one activity to another is one of their key advantages.

A variant of RNNs [16] designed to circumvent the "long-term dependence" problem and to learn Archiving and recalling information over extended periods of time is termed "long" STMs, or LSTM. The "cut" of an LSTM is made up of a cell or "node", an input gate, an output gate, and a "forget" gate. For the input/output gates to synchronize the knowledge flow, this node then gathers the account values while taking into consideration predetermined time intervals.

A relatively recent design that pits two neural networks against one another is called Generative Adversarial Networks (GANs) [17]. Though the second network assesses the authenticity of data (whether it is part of the significant training dataset), the first network creates artificially realistic data. In numerous fields, including genetics, GANs have demonstrated their ability to improve classification accuracy [18].

One of the most widely used deep learning models in unsupervised learning, the Auto Encoder (AE) usually, unlike most learning processes, begins with an 'encoder' that forms the data by teaching the network how to 'strip the signal's "noise" [19]. Simple non-linearities, in which a non-linear function is applied to the scalar output of a linear filter, are commonly used in neural nets.

A group of neurons models a portion of the input by activating a small fraction of its features in capsules, which employ more complex non-linearity [20]. Capsules in the CapsuleNet suggested in [21] are dependent on kernels but not on one another. One of the most current Deep Learning model architectures has not yet undergone substantial testing by the scientific community. The architectures of the most popular Deep Learning models are shown in Figure 1.

The deep learning techniques can beat the most recent techniques in most genomic problems. Furthermore, genomics offers highly diverse data, and deep learning can handle multimodal data efficiently, making it a strong contender to achieve precision medicine. However, it has taken a very long time to convert the knowledge gained in genomics into tools that are useful in clinical settings.

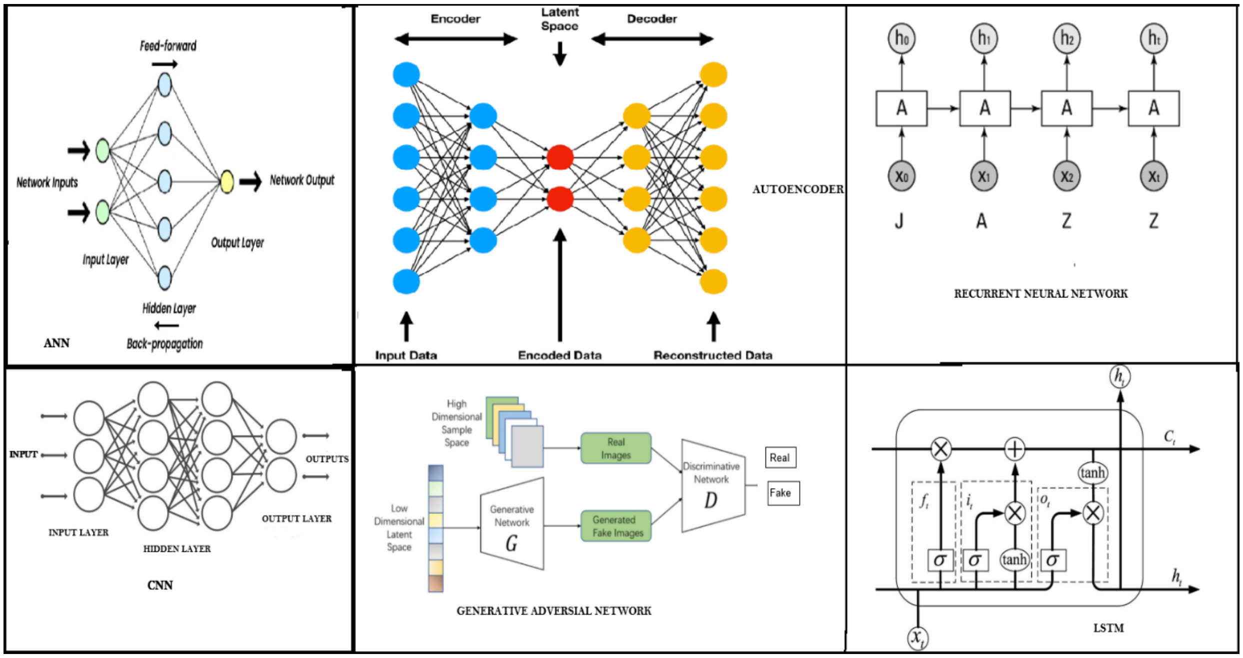

Figure 1. Architecture View of Several Deep Learning Methods

To enhance the use of Deep Learning genetics in prediction and prognosis, more work should be done to examine and integrate datasets, both public and private. Moreover, explainable Deep Learning models can open the door to the discovery of regulatory connections in a variety of pathological circumstances, including tissues and disease states, in addition to new biomarkers.

3.1 Anatomy of the Skin with Different Levels of Burn Injury

Burns are first, second, or third degree based on how deep and how difficult penetrations to the skin are, as shown in Figure 2.

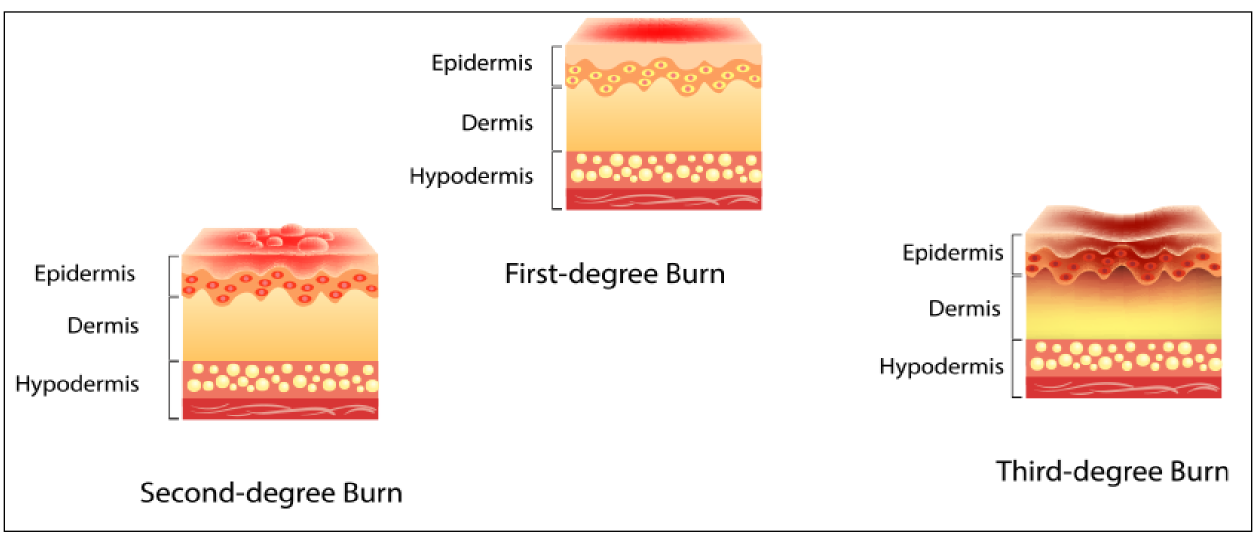

Figure 2. Classification of Skin and its Structure Representation

3.1.1 First Degree (Superficial)Burns

The epidermis, commonly known as the skin's outermost layer, is always harmed by superficial burns; the affected area becomes red, patchy, dry, and bubble-free. A mild sunburn is typically used as an example. This kind of sunburn is uncommon and typically only results in a change in skin tone rather than long-term tissue damage.

3.1.2 Second Degree (Partial Thickness) Burns

Second degree burns affect the epidermis and part of the dermis-skin layer. The site of the burn is painful, swollen and noticeably red with blisters.

3.1.3 Third Degree (Full Thickness) Burns

Burns that are third degree are advanced and more severe as deep as the dermis as well as epidermis are burned. B bones, muscles and the tendons beneath are also exposed to damage due to third degree burns. The burn site looks burned or white. Because the nerve endings are gone, the area is devoid of feeling. In addition to being physically debilitating, a serious burn can also be emotionally damaging [22]. Both the burn victim and the entire family may be impacted. Scarring, deformity, loss of mobility, loss of limbs, and recurrent infections are among the physical skills that people with severe burns may lose because their skin is less able to fight off infections. Furthermore, severe burns can pierce deep skin layers and injure muscle or tissue, which might have an impact on any bodily system.

Just like mental stress, burns also come with the consequences of causing certain “depression” with the possibility of a “traumatic” disorder, or “flashes” back to the time of the occurrence. Psychologically, the impact of a burn could be worse if everything in the fire together with a loved one was lost. The process contains in order Haemostasis (coagulation), inflammation (mononuclear cell infiltration), proliferation (epithelialization, fibroplasia, angiogenesis and formation of granulation tissue), and maturation (collagen deposition or formation of scar + tissue), which are the four overlapping classic phases that form the systematic process of skin healing. The origins of the burn, the extent and size of the burn, the patient's overall health, and the kind of graft or materials used to cover burn wounds are some of the variables that affect skin healing following burn injuries.

The first stage of healing depends mostly on how deep and extensive the area of the burn is. For a first-degree burn, a person would expect to heal within two weeks, and the amount of scaring or damage would be negligible. For even more severe burns, the epithelial surface begins to heal and re-cover within a few days and burns of partial thickness will heal due to the rapid keratinocyte migration from the skin appendages within hours of the damage. Because deeper burns require quick wound closure, healing starts around the margins but not in the middle. Dendritic cells release several substances that promote proliferation, which guarantees quick burn healing. Consequently, substances that enhance dendritic cells are thought to be medicines for enhancing burn wound care. Hypoxia-inducible factor 1 and angiogenic cytokines like VEGF and CXCL12 trigger angiogenesis during burn healing, which is maintained by an increase in endothelial progenitor cell blood levels that correspond to the damaged skin area. The initiation of the TGF-β pathway always guarantees an increase in contraction, which may result in tissue remodelling and skin scarring.

Burns, in contrast to other types of wounds, can potentially damage almost every single system in the body: the lungs, the kidneys, the heart, the liver, the gastrointestinal tract, the bone marrow, and even the lymphoid organs, leading to functional syndrome and multiple organ failure [23]. The concentration of inflammatory mediators at the burn site, such as interleukins 6, 8, and 1-beta and tumours necrosis factor alpha (TNF-α), which have systemic effects, is correlated with the area of the burn surface in serum. Elevated levels are thought to raise the risk of death, infections, and multi-organ dysfunction syndrome.

The skin healing response is the coordinated signalling that repairs damaged tissue after a skin injury. The three stages of this skin reaction’s development are the inflammatory, proliferation, and maturation phases. After four days and starts with blood clotting, this leads to fluid loss and a blood clot that temporarily protects against infections. Increased vascular permeability brought on by local inflammatory chemicals (activated complement, histamine, etc.) causes swelling and redness. A sudden increase in blood flow in the vicinity of the lesion is encountered after this. That results in the production of a fibrin matrix and plasma extravasation. To remove the deadly tissue and manage infections, monocytes, neutrophils and other immune-competent cells infiltrate this matrix [24].

Between days 5 and 20 of the wound healing phases, as blood vessels form, and thanks to inflammatory cells, the proliferation of vascular cells and fibroblasts begin due to the release of certain "growth factors". Subsequently, the vascular fibroblasts begin to liberate the colonies of collagen, replacing the framework of fibrin. Myofibroblasts, as constituents of granulation tissue, will often form fibroblasts, and due to the expression of actin, the wound will contract and shrink. This also promotes the formation of "granulation tissue". From there, the keratinocyte migration begins, and is the final step, this occurs when the surface of the granulation tissue, which is covered with a blood clot, is reached [25].

3.2 Wound Healing and Deep Learning Process

In literature, one can cautiously state there are three stages in wound healing, see for example [26]. at the same time, we must understand these stages do not follow a linear pathway but are concurrent. Within Phase 1 (inflammation phase) there is haemostatic inflammation, which includes damage control wound- cleansing characterized by the activation of platelets, their degranulation, the formation of a clot, the activation of a cascaded clotting pathway, the formation of a fibrin clot to seal the wound, the formation of a fibrin matrix which provides a temporary scaffold for the inflammation cells, and the release of cytokines which attracts the inflammatory, mesenchymal, and endothelial cells to the wound. The acceleration of collagen formation triggers granulation tissue, while collagen is also reepithelialised, angiogenesis and fibrogenesis are enhanced, adnexal structures are restored, and the architecture of the skin is restored (the macrophages are switching from M1 to M2), while the matrix is extracellularly produced and secreted. also, the type III collagen, and type III to type I collagen, are found to be increased. The final phase, the remodelling phase, cross a threshold and completes the scar by re-epithelializing the occlusive wound and wound bed. The remodelling of matrix, including proteolytic collagen types, activities type I collagen extra matrix synthesis and secretion, and restores the type I/type III collagen ratio to the physiological balance

Fourth, numerous factors affect the outcome of healing including the severity, depth, and area of the wound as well as the anatomical site, skin thickness, skin adnexal structures density, biotic and non-biotic aspects, healing time, age and the genetic and epigenetic background of a person, the presence of other diseases, wound microbial contamination, and the microenvironment changes caused by multiple tissue injury.

4. RESULTS AND DISCUSSIONS

This methodology shows the segmentation of burn wound assessment and performance measures and compares our method with all other state-of-the-art outcomes. The approach begins with pre-processing the images from the training dataset, after which burn segmentation, posture estimation, ROI extraction, and feature extraction are carried out. Extensive tests were conducted to confirm the effectiveness of this strategy. Figure 3 provides an explanation of the general strategy. Additionally, we used the training dataset to train our deep learning network. Skin Burn Dataset is a niche set of around 1,300 high-resolution images, each carefully annotated to depict different levels of skin burns. While the Image-based Features include Colour Features, Redness / Erythema intensity, Presence of white/charred areas, Yellow or brown discoloration (infection/necrosis), Extracted using RGB / HSV colour histograms, the Deep Learning Features are extracted automatically using CNNs / pre-trained models (ResNet, VGG, etc.) that capture complex patterns not visible by handcrafted features. The images were web-scraped and hand-curated to offer a variety of visual representations of burn injuries, which makes the dataset particularly useful in medical research, healthcare Al model training, and education.

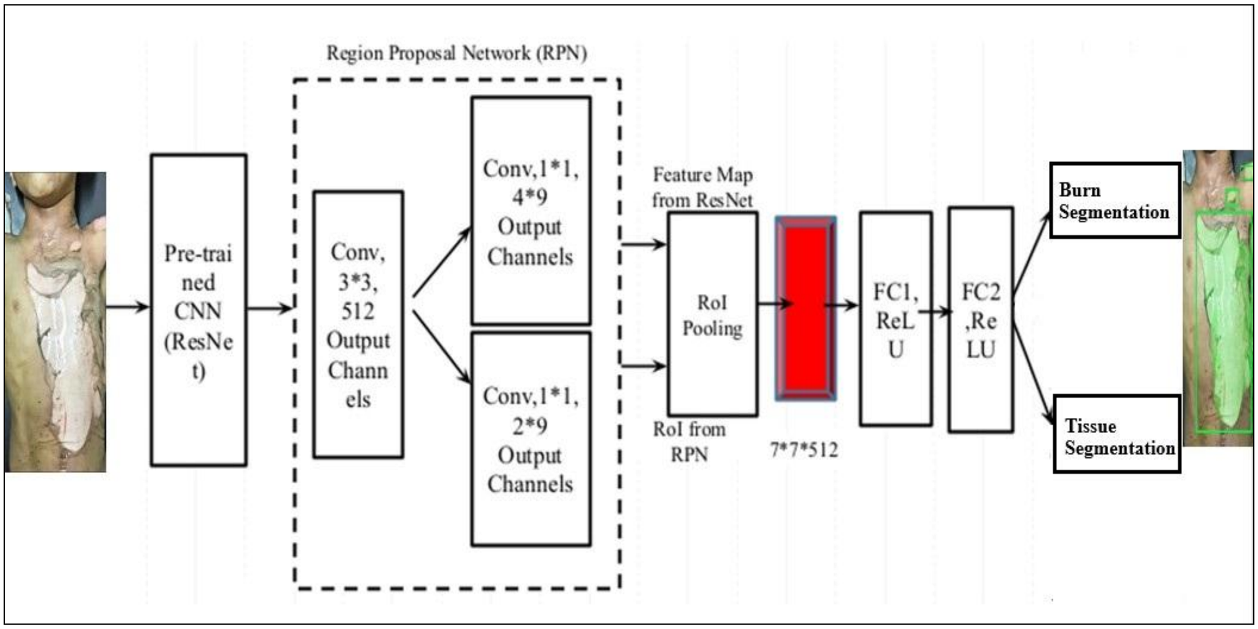

Figure 3. Deep Learning Model to Segment Burn Image

5.1 Implementation Setup

This suggested approach implements a CNN to segment the skin burn images. This CNN works by replacing the foundational convolutional layer by depth-wise in which each layer can be classified to point-wise convolutional layer and a depth-wise convolutional layer.

Step 1: We have used several training techniques, including U-Nets, DeepLab, FCN, and SigNet, to train the burn picture dataset. Bring in the necessary libraries, including Keras.

Step 2: Adjust the variables and data generator after importing the libraries. Image Data Generator are used for generating batches of images and augmentation like rescaling the images can be done based on the size of the dataset.

Step3: The data set can be pre-processed and divided using a data generator.

Load the models with the data to train them. For compact models, CNN with a depth-wise convolutional layer applies a convolutional filter to each input channel. A point-wise convolution is a 1 X 1 convolution wherein the input channel is subjected to a linear combination to form new features.

Step 5: The model includes an encoder-decoder. The encoder is constructed using the depth-separable convolution block. Among its six layers are batch normalization, ReLu activation, and a three-layer depth-wise convolutional layer.

Step 6: Batch normalization followed by a 1x1 point-wise convolution sheet and ReLu comes next. ReLu6 was the activation feature that was used. Multiscale spatial pyramid pooling captures the encoded features and is complemented with higher level features from a bilinear up-sampling layer and a pooling layer.

Step 7: The final output is obtained by concatenating the features, refining them using a couple 3X3 convolutions, and then doing a straightforward bilinear up-sampling by a factor of 4.

Step 8: A dropout layer is placed immediately before the output layer in each bottleneck block, after which a batch normalization layer is added.

Step 9: During the post-processing phase, segmentation masks are produced first by thresholding with a preset threshold of 127, which is a binary value. Our model predicts grayscale images with pixel value ranges from 0 to 255 as raw segmentation masks.

Step 10: The binary masks undergo additional processing, such as hole filling and tiny region removal, to produce the final segmentation masks.

Step 11: The binary masks undergo additional processing, such as hole filling and tiny region removal, to produce the final segmentation masks.

Step 12: Similarly, small false-positive sounds are muffled. The dataset's photos are taken from the raw image for every wound. Thus, by deleting the connected portion that is sufficiently tiny, we can easily remove noise from the segmentation results using adaptive thresholds.

Step 13: To evaluate segmentation outcomes, three metrics are used: precision, recall, and the dice coefficient.

5.2 Evaluation Metrics

The evaluation metrics like dice coefficient, precision and recall of image segmentation can be computed as follows to assess its performance.

- Precision
  Segmentation precision is demonstrated by precision. More specifically, precision is a statistic that determines the proportion of pixels in segmentation that are successfully segmented. It is computed as follows as in Equation (1).

$$Precision = \frac{TruePositives}{TruePositives + FalsePositives} \tag{1}$$

- Recall
  Recall is another indicator of segmentation accuracy. It determines the proportion of accurately segmented pixels in the ground truth and tests that proportion as expressed in Equation (2).

$$Recall = \frac{TruePositives}{TruePositives \ + FalseNegatives} \tag{2}$$

- Dice Coefficient (Dice)
  Dice are used to illustrate the relationship between the ground truth and its segmentation result. Dice is another name for the F1-score, which is a metric that strikes a compromise between precision and recall. To compute dice, take the precision and recall harmonic means as formulated in Equation (3).

$$Dice = \frac{2\times TruePositives}{2\times(TruePositives+FalsrPositives+FalseNegatives))} \tag{3}$$

5.3 Experimental Setup

The deep learning model was implemented in Python in the work that was presented, with Keras and Tensorflow serving as the backend. To expedite the process, the models were trained on a 64-bit Ubuntu PC equipped with a single NVIDIA RTX 2080Ti GPU and an 8-core 3.4 GHz CPU. We employed binary cross entropy as the loss function, and precision, recall, and dice score served as the evaluation matrices. Only two photos were included in each mini-batch, and the starting learning rate was chosen at 0.0001 to balance training accuracy and performance. A single epoch took roughly 77 seconds to practice, and our network's convolutional kernels were initialized utilizing HE/Xavier initialization to expedite the training procedure. We employed early stopping to terminate the training when the dice score remained unchanged for over 100 epochs. We trained our deep learning model for 1000 epochs prior to over-fitting.

5.4 Evaluation Results

The overall effectiveness of the proposed process is evaluated by contrasting the segmentation outcomes produced by our techniques with those produced by FCN-VGG, SegNet, and Mask-RCNN. Due to its exceptional segmentation performance on biological pictures using a comparatively limited training dataset, we employed 2D U-Net in the comparison. From the Tables, it is clear that higher parameters usually better precision/recall/dice, but only up to a point, Over-parameterized models can over-fit (good training scores, poor test scores), Under-parameterized models may underfit (low precision/recall/dice), Dice score is most sensitive to recall drops (missing true burn pixels lowers dice more than precision errors). In burn classification/segmentation: Light models (few parameters) are useful for speed but sacrifice dice; Medium models (U-Net) balance between computation and performance to be maintained; Heavy models (DeepLab, FCN) can push precision/recall higher but risk over-fitting and requires need large datasets. The methods employed for each comparison model are identical, and Tables 1 and 2 present the findings, respectively.

Table 1. Comparative Analysis of Total Number of Trainable Factors

Description	Mask- RCNN	MobileNetV2	U-Net	SegNet	FCN-VGG16
Number of Parameters	72,631,718	3,121,105	5,734,939	1,002,561	142,274,631

Table 2. Performance Analysis of Deep Learning Models

Model	Mask-RCNN (%)	VGG16 (%)	SegNet (%)	U-Net (%)	MobileNet V2+CCL (%)
Precision	99.04	79.74	71.63	87.64	94.14
Recall	88.30	81.39	74.17	82.13	95.17
Dice	94.20	78.74	73.74	85.11	95.15

5.5 Future Scope: Skin Tissue Engineering

Genomics, the field of study that examines an organism's entire complement of DNA, provides information about genetic dispositions that can affect wound healing and vulnerability to complications, and can reveal genetic variations and mutations that affect skin repair. A clearer mechanistic insight into the gene regulatory networks of regeneration processes may potentially allow for their targeted reactivation as a strategy to heal human injury and degeneration. Stem cells and miRNAs from different cell types have been found to promote recovery from burn wounds by facilitating healing, reducing inflammation, and inhibiting the formation of scar tissue [27, 28]. Tissue regeneration technologies augment skin repair by processes such as re-epidermalization and angiogenesis, which greatly enhance the success rates of skin healing for burns.

Multiomics, which is an integration of genomics, transcriptomics, proteomics, and metabolomics, gives insights into the molecular processes of skin regeneration and repair and aids in discovering new therapeutic targets. Skin healing is traditionally said to take place in four phases; these phases are haemostasis (coagulation), inflammation (mononuclear cell infiltration), and in that order also include proliferation (which contains fibroplasia, angiogenesis, and formation of granulation tissue) and maturation (which contains fibroplasia, angiogenesis, and formation of granulation tissue). The cause of the burn, the extent and size of the burn, the patient's overall health, outside variables, and the kinds of particles used to cover burn wounds are some of the variables that affect skin healing following burn injuries.

The skin heals in different ways depending on the extent of the burn. Surface burns do not leave scars and heal in two weeks while partial thickness burns re-epithelialize in hours due to keratinocyte migration from the skin dermal appendages. Burns of greater depth heal in the edges, rather than the centre. They heal faster due to the need of quick closure of the wound. The extent of the wound determines the methods, which include grafting and cell therapy to aid burn patients. Besides categorizing burn injuries, the proposed model using deep learning algorithms, prescribes the most suitable ways to treat the burns. After assessing the severity of the burn wounds, the model provides and analyses various suitable approaches to optimize the healing process. This, in return, provides much relief to the healers and patients in determining the most effective treatment.

5. CONCLUSION

Burns are not a single wound; rather, they are a sign of a more serious issue. Burn wounds heal similarly to other wounds, although several systemic variables interact significantly during this process. The patient's overall health has a direct impact on the burn site, which can result in situations like septicaemia and even death. Long-term hospitalization can lead to other burn care issues, like increased hospital expenses, and is a terrible experience for victims and their families. Long hospital stays may also be attributed to treatment delays brought on by a lack of access to local burn centres and suitable objective evaluation methods. Depending on the extent of the injury, our suggested model provides a high prediction score for burn wounds that can heal with the right medical care.

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AUTHOR CONTRIBUTIONS

C. Pabitha: Conceptualization, Data Curation, Methodology, Writing – Original Draft Preparation;
K. Revathi: Project Administration, Writing – Review & Editing;
R. Krishna Priya: Writing – Review & Editing.

CONFLICT OF INTERESTS

No conflicts of interests were disclosed.

ETHICS STATEMENTS

This research did not involve human participants; data are taken from a defined dataset available or human tissue. Therefore, ethical approval and informed consent were not required for this study.

DATA AVAILABILITY

The data that support the findings of this study are openly available in Kaggle at http://doi.org/ [-]. These data were derived from sources in the public domain [https://www.kaggle.com/datasets/shubhambaid/skin-burn-dataset].

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BIOGRAPHIES OF AUTHORS

	**C. Pabitha** is working as an Associate Professor in SRM Valliammai Engineering College, Chennai. She has completed Ph.D. in Information and Communication Engineering from Anna University, Chennai in the year of 2022. Secured 17 years of teaching experience and published 20 research articles in reputed journals and international conferences. Her research focuses on Artificial Intelligence, Machine Learning, Deep Learning, Computer Vision, Image Processing. She can be contacted at email: pabithac.cse@srmvalliammai.ac.in.
	**K. Revathi** is now the Associate Professor in the Department of Information Technology of SRM Valliammai Engineering College Chennai located in Tamil Nadu in India. She pursed Ph.D. in Information and Communication Engineering from Anna University Chennai in the year of 2022. She received PDF from Shinawatra University in Thailand by the year of 2025. Artificial Intelligence, Internet of Things and Data Science are the focus of her research. She has 16 years of teaching experience across different institutions. To her credit she has published 29 research papers in international high impact factor journals and conferences. She can be contacted at email email: neyadharshini@gmail.com / revathik.it@srmvalliammai.ac.in.

	**R. Krishna Priya** expertise is complemented by a bachelor's degree in computer science from VELS Institute of Science and Technology and a master's in data science from SRM Valliammai Engineering College. Currently, she serves as an Assistant Professor at Sairam Engineering College, where she teaches and mentor students in data science, machine learning, and computer science, while contributing to curriculum development and guiding practical projects. Prior to this, she worked as a Data Analyst at HTC, applying my skills in Python, SQL, Power BI, and Tableau to analyze data and support business initiatives. She can be contacted at email: 2001krishnapriya07@gmail.com.