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Skin Burn Detection using Image Processing

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Abstract: *Skin cancer at its early stages can be cured. But when it is not recognized at its early stages, it begins to spread to other parts of the body and can be deadly. Benign Melanoma is simply appearance of moles on skin. A normal mole is usually an evenly coloured brown, tan, or black spot on the skin. It can be either flat or raised. Skin burns are the deadly form of cancers in humans. If skin burns are detected at early stages, it can be cured completely. So, an early detection of skin cancer can save the patients. Skin burns are of two types- Benign and Malignant Melanoma. Benign melanoma is not a deadly condition, but malignant melanoma is a deadly form. Both resemble same in appearance at the initial stages. Only an expert dermatologist can classify which one is benign and which one is malignant. The CNN based Classification methodology uses Image processing techniques. Main advantage of this computer-based CNN classification is that patient does not need to go to hospitals and undergo various painful diagnosing techniques like Biopsy.*

Keywords: Convolutional neural network, Image processing, Deep learning

I. INTRODUCTION

For a successful evolution of a burn injury, it is essential to initiate the correct first treatment. To choose an adequate one, it is necessary to know the depth of the burn, and a correct visual assessment of burn depth highly relies on specialized dermatological expertise. As the cost of maintaining a burn unit is very high, it would be desirable to have an automatic system to give a first assessment in all the local medical centres, where there is a lack of specialists. The World Health Organization demands that, at least, there must be one bed in a burn unit for each 500000 inhabitants. So, normally, one burn unit covers a large geographic extension. If a burn patient appears in a medical centre without burn unit, a telephone communication is established between the local medical centre and the closest hospital with burn unit, where the non-expert doctor describes subjectively the colour, shape, and other aspects considered important for burn characterization. The result in many cases is the application of an incorrect first treatment (very important for a correct evolution of the wound), or unnecessary displacements of the patient, involving high sanitary cost and psychological trauma for the patient and family.

II. LITERATURE REVIEW

Aliyu Abubakar, Hassan Ugail, Ali Maina Bukar, In this paper the rapid and accurate assessment of burn injuries is a very challenging task in burn surgery. To illustrate the potential of millimeter-wave systems for burn diagnosis, the current paper at first shows a coaxial probe based ex-vivo measurement of the effective relative permittivity of skin depending on the degree of burn and also in-vivo measurements of the relative permittivity change caused by small skin irrita- tion (i.e., increased or decreased blood perfusion, edema formation) in the frequency range 0.1 to 50 GHz. [1] .

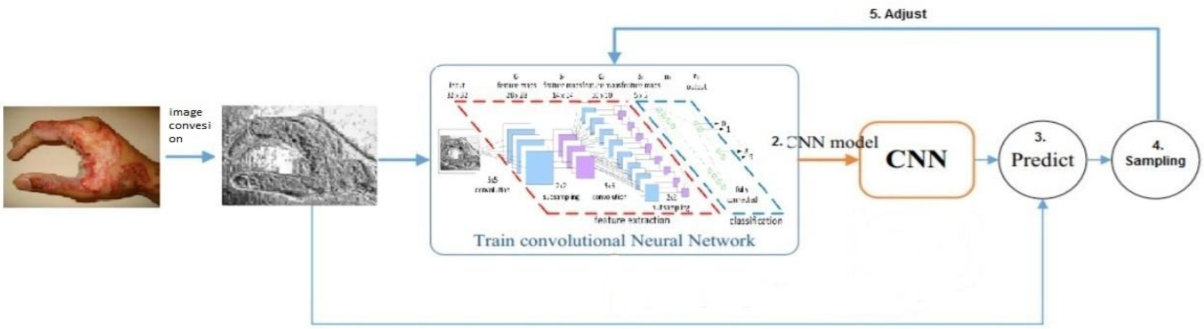
JPedro Castro, Efficient biochemical characterization of skin burn healing stages can im- prove clinical routine to adjust patients' treatment. The golden standard for diagnosing skin burning stages is the histological biopsy. This practice is often expensive and tech- nically challenging. There have been advances in the treatment, and diagnostic of the critical skin burned patients due to the increase of multidisciplinary collaboration in the paper. Alireza Madannejad, Javad EbrahimiZadeh, Fatemeh Ravanbakhsh, this paper provides a novel solution for increasing the difference between the contrast of permittivity of normal skin and burnt skin using injected saline. The paper makes use of injecting saline water into healthy tissue surrounding the burnt part to increase the conductivity contrast of the healthy tissue compared to the burnt area [3].

Yuan Gao and Reza Zoughi, Accurate skin degree-of-burn assessment is critically important and can assist burn technicians and physicians to make appropriate treatment decisions. Mil- limeter wave imaging is a potential diagnosis tool capable of distinguishing between healthy and burned skin as the dielectric properties of the latter is significantly [4].

Mikhail Golovkov, the results of experimental arc testing of Arc Rated FR fabric with three dif- ferent geometrical arc electrode arrangements are presented and discussed. The testing was done using: a) “open air” apparatus for fabric panel test methods ASTM F1959 and IEC 61482-1-1 with vertical butted arc electrodes in open air; b) “box” apparatus for test method IEC 61482-1-2 with vertical butted arc electrodes placed in a box; c) nonstandard “ejected arc” apparatus with parallel horizontal arc electrodes in open air [5].

Daniel Oppelt, Tim Pfahler, Felix Distler, in modern burn surgery the fast and precise assessment of the burn depth is challenging but also of high importance to adapt the correct wound care. A con- tactless nearfield probe operating at frequencies from 75 to 110 GHz is presented that is sensitive to the hydration of the skin layers, which is correlated to the burn depth.[8]

II. PROPOSED METHODOLOGY



2.1 Module

A. Prepossessing

In this Module Machine will be processing on given Input. In prepossessing machine will train the data-set, removing Noisy part of given input and then resize the data-set.

B. Feature Extraction

In this module user will give age, body, etc. that attribute give to machine. The feature Extraction technique gives us new features which are a linear combination of the existing features. The new set of features will have different values as compared to the original feature values. The main aim is that fewer features will be required to capture the same information.

C. Classification

CNN Algorithm (Convolutions Neural Network)

CNNs are powerful image processing, artificial intelligence (AI) that use deep learning to perform both generative and descriptive tasks, often using machine vison that includes image and video recognition, along with recommender systems and natural language processing (NLP).

One of the main parts of Neural Networks is Convolutional neural networks (CNN). They are made up of neurons with learnable weights and biases. Each specific neuron receives numerous inputs and then takes a weighted sum over them, where it passes it through an activation function and responds back with an output.

There are Four types of layers in Convolutional Neural Networks:

1. **Convolutional Layer:** In a typical neural network each input neuron is connected to the next hidden layer. In CNN, only a small region of the input layer neurons connect to the neuron hidden layer.

2. **Pooling Layer:** The pooling layer is used to reduce the dimensionality of the feature map. There will be multiple activation pooling layers inside the hidden layer of the CNN.
3. **Flatten:** Flattening is converting the data into a 1-dimensional array for inputting it to the next layer. We flatten the output of the convolutional layers to create a single long feature vector.
4. Fully-Connected layer

Performance analysis obtained from the test data with proposed CNN machine learning approach.

Machine Learning Models	Without Augmented Dataset				With Augmented Dataset			
	Acc.	Prec.	Rec.	F1-sc.	Acc.	Prec.	Rec.	F1-sc.
Random Forest Classifier	0.773	0.784	0.734	0.744	0.804	0.81	0..807	0.809
Support Vector Machine	0.767	0.762	0.740	0.747	0.78	0.785	0.781	0.778
Decision Tree	0.706	0.692	0.692	0.692	0.714	0.715	0.725	0.712
K-Nearest Neighbor	0.661	0.796	0.571	0.517	0.696	0.698	0.698	0.684
Logistic Regression	0.642	0.619	0.601	0.601	0.653	0.654	0.655	0.623
Multi-Layer Perceptron	0.530	0.595	0.580	0.524	0.56	0.565	0.564	0.543

The proposed CNN architecture has been slightly modified with hyperparameter tuning in four different ways to explore the best performing model for burn depth prediction where each method has executed over 30 epochs for training. Also, the accuracies and losses fluctuate slightly after 25 epochs for all the models, indicating that the models have converged.

III. CONCLUSION

In this system we are going to use Convolutional Neural Network (CNN) algorithm for the degree of skin burn image recognition. In the previous system KNN and SVM algorithm is used which gives lower accuracy. For that we are going to implement this system with CNN algorithm to improve accuracy and accurate results. This burns analysis will be helpful for remote hospital in Vietnam where the hospital service must be improved

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