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AI-WOUND ASSESSMENT



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ABSTRACT

Nearly one-third of the world's population lacks access to essential healthcare. Wound care is one of the largest issues that healthcare providers face. This shortage can reach severe levels in developing countries, especially in war times as happening now in Gaza. Our research presents a web-based deep-learning application that classifies wound types and their healing time based on images using residual neural networks (ResNet) and also we introduce a tool that helps medics in Gaza decide which wounds deserve more attention to deal with during the shortage of medical supplies.

PROBLEM DEFINITION

- The demand for medical workers is rising as the global population grows.
- In 2020, the global shortage of medical workers was 15 million, and it is anticipated the world will continue suffering from this shortage till 2030
- Wars and pandemics like COVID-19 highlight how critical it is to find long-term solutions.
- Wound care is one of the most required healthcare services.
- PDES that model wound healing are complex, so researchers have tried to use deep learning to predict wound healing time.

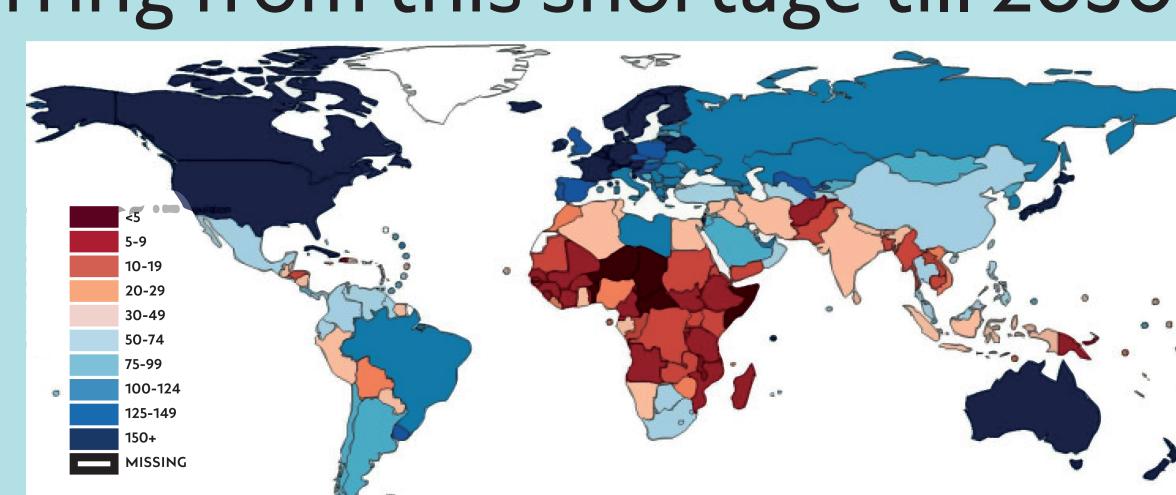


figure 1: Health workforce per 10,000 population

AIM In this research we aim to classify wounds and their healing time and introduce a tool to medics in Gaza to help them assess wounds amid the scarce medical supplies.

METHODOLOGY

- Our dataset is made of 1500 wound images collected from online public datasets labelled with their classes.
- We then applied data augmentation techniques to increase the size
Pre-trained ResNet Classifier was trained on 80% of the dataset and 20% was left for testing.

Architecture Overview(figure2):

Input Layer: Original input image.

Convolutional Layers: A series of convolutional layers with batch normalization and ReLU activation.

Residual Blocks: Key building blocks with skip connections, enabling the training of very deep networks.

-Block 1 to Block 16: Sequential residual blocks.

-Convolutional Layer 1: Convolutional operation with batch normalization and ReLU.

-Convolutional Layer 2: Subsequent convolutional layer with batch normalization and ReLU.

-Skip Connection: Identity mapping to preserve gradient flow.

Network Depth: 34 layers, including convolutional, batch normalization, and fully connected layers.

Output Layer:

-Global Average Pooling Layer: Condenses spatial dimensions.

-Fully Connected Layer: Produces final classification output.

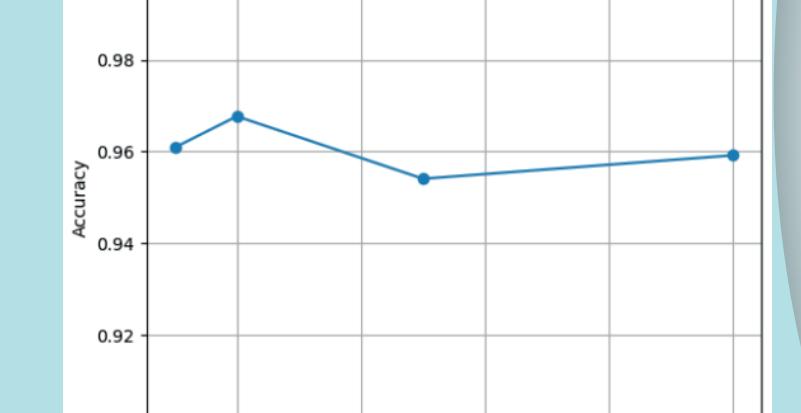
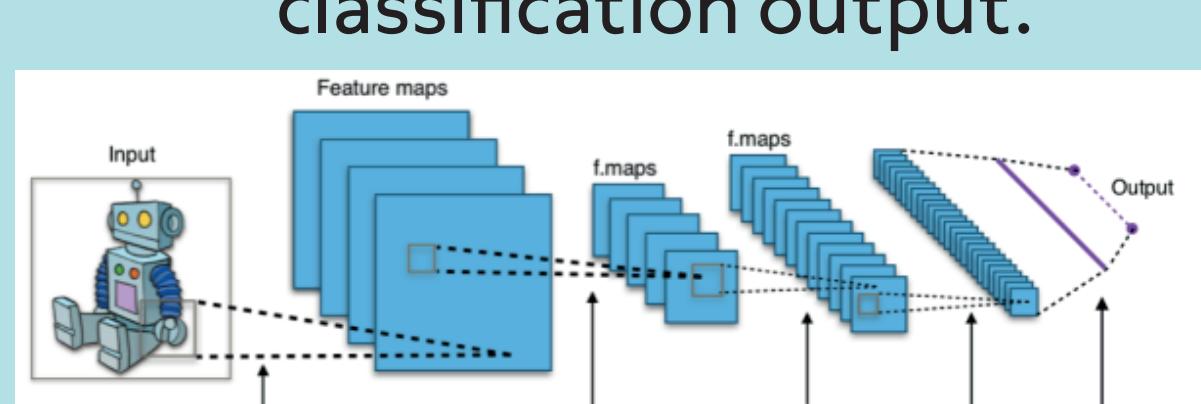
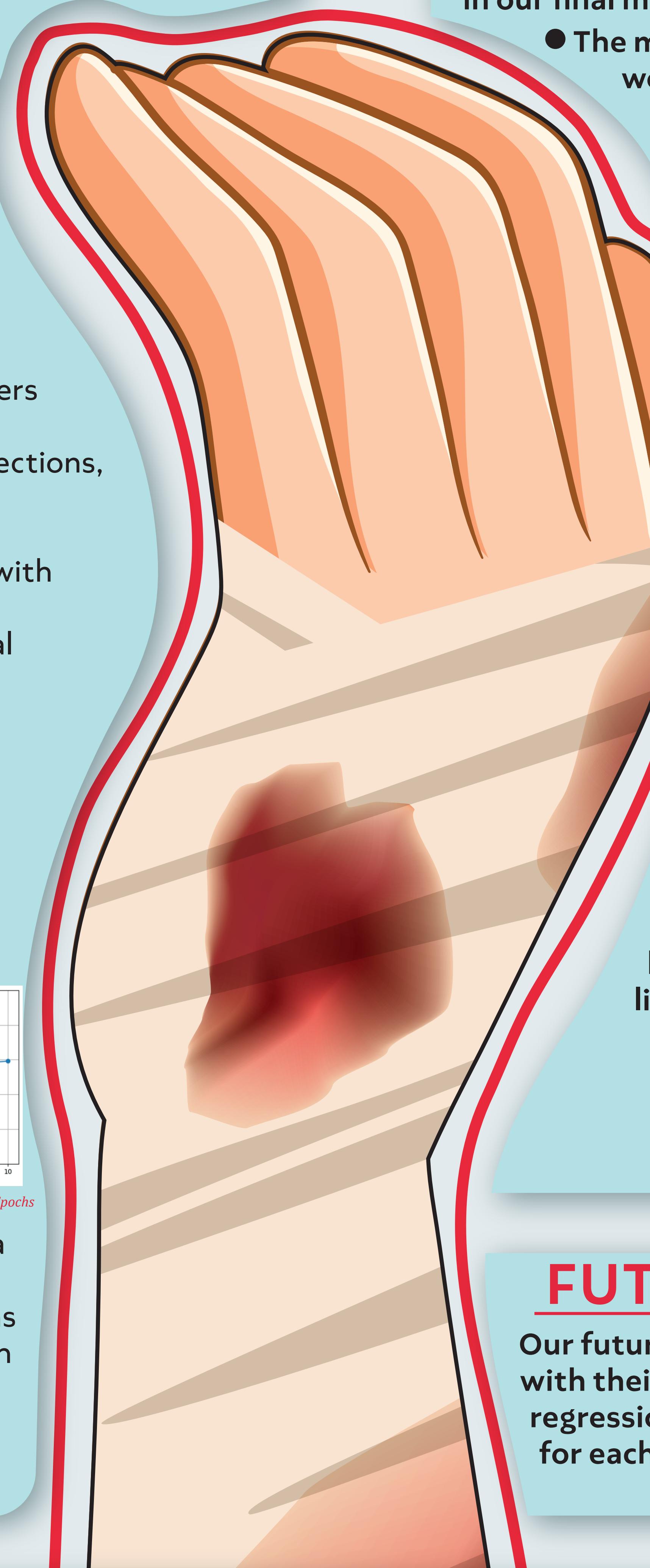


figure 3 : Accuracy vs No.Frozen Training Epochs

- To provide medics with a wound priority list, we used a subset of our dataset with 120 images. wound classes encountered in war zones such as burns and lacerations were chosen. Each wound was assigned attributes such as severity , depth, etc. to determine its priority.

- This priority is determined by a score representing a linear combinations of the attributes' values of each wound.



CONCLUSION

In this research, we aimed to address the lack of primary wound care worldwide with a specific interest in the impact of this shortage in war zones. We first explored the possibility of obtaining wound healing time using partial differential equations and then decided to depend on the classification of the wound types to get an average healing time. We used the ResNet classifier and obtained a 96% accuracy on our dataset. Healing time was used along with other significant wound attributes such as depth and severity to assess the priority of wounds to help medics in war zones during the shortage of medical supplies.

PIPELINE FLOWCHART

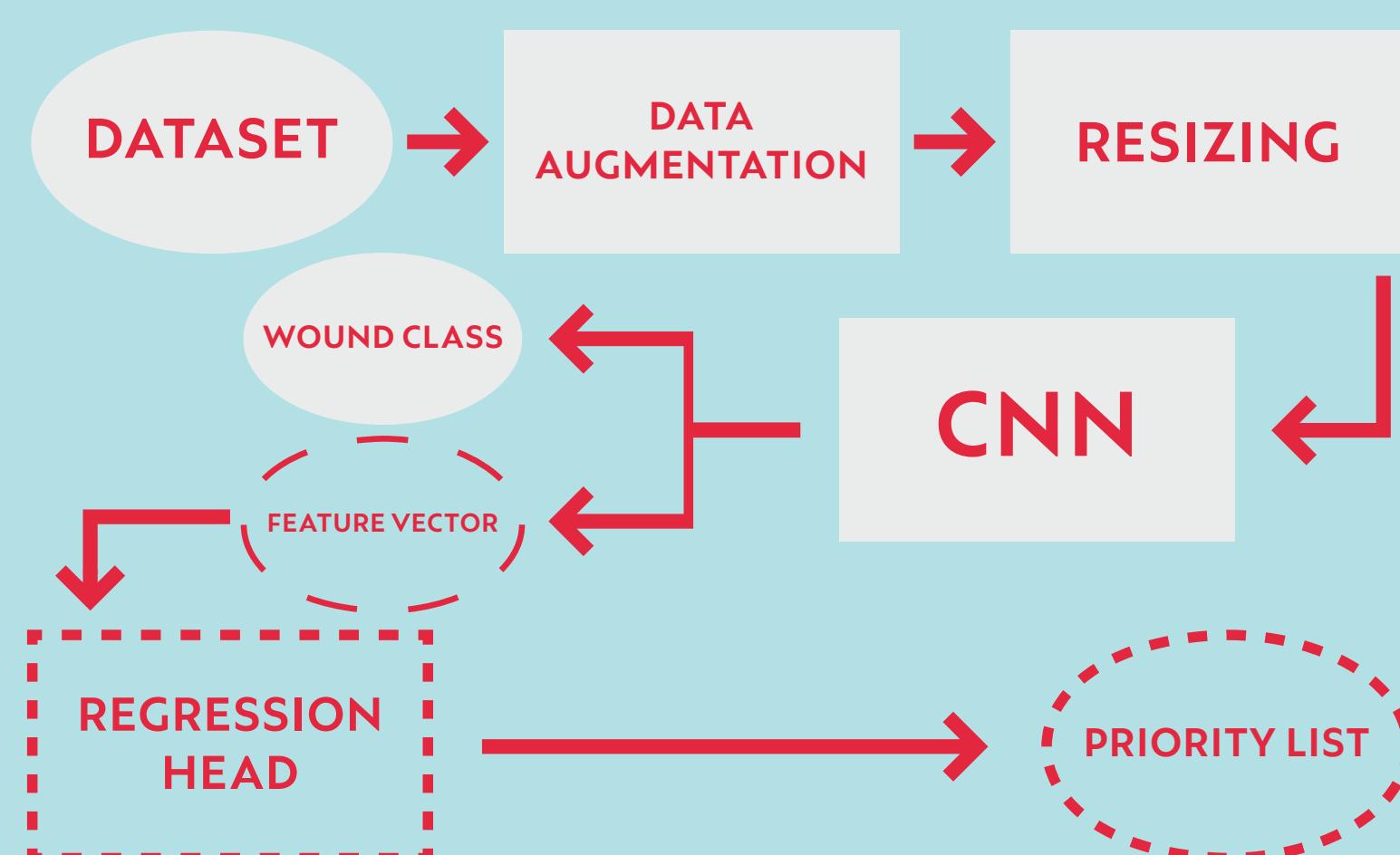


figure4 : Development pipeline

RESULTS & ANALYSIS

- We determined that the number of frozen iterations doesn't greatly impact the accuracy of the model, so we stuck with 2 frozen iteration in our final model.

- The model achieved an accuracy of 96% at classifying the wounds.

The model experienced a slight difficulty at differentiating diabetic and pressure wounds, for a total of 10 misclassifications out of the 1030 images in those 2 classes.

We can also see (figure5) that the model had no problem at all at classifying cuts, with a 100% accuracy in our dataset.

	Abrasions	Blisters	Burns	Cuts	Diabetic Wounds	Lacerations	Normal	Pressure Wounds	Surgical Wounds	Venous Wounds	Total
Abrasions	161	0	2	0	0	0	0	0	0	0	165
Blisters	0	219	0	0	0	0	0	0	0	0	219
Burns	2	0	130	0	0	0	0	0	0	0	132
Cuts	0	0	0	94	0	0	0	0	0	0	94
Diabetic Wounds	0	0	1	0	481	0	0	0	0	0	482
Lacerations	0	0	0	0	0	119	0	0	0	1	120
Normal	0	0	0	0	0	0	194	0	0	0	194
Pressure Wounds	0	0	0	0	0	0	0	35	0	2	37
Surgical Wounds	0	0	0	0	0	0	0	0	2	415	417
Venous Wounds	0	0	2	0	0	0	0	0	0	0	2
	Abrasions	Blisters	Burns	Cuts	Diabetic Wounds	Lacerations	Normal	Pressure Wounds	Surgical Wounds	Venous Wounds	Total

figure5 : Confusion matrix for 10 different wound classes

- Our model, however, might be subject to overfitting, as the dataset didn't contain enough images.

We deployed our model in a web application. The user can upload an image and get the wound type and average healing time. The priority list feature is also available.

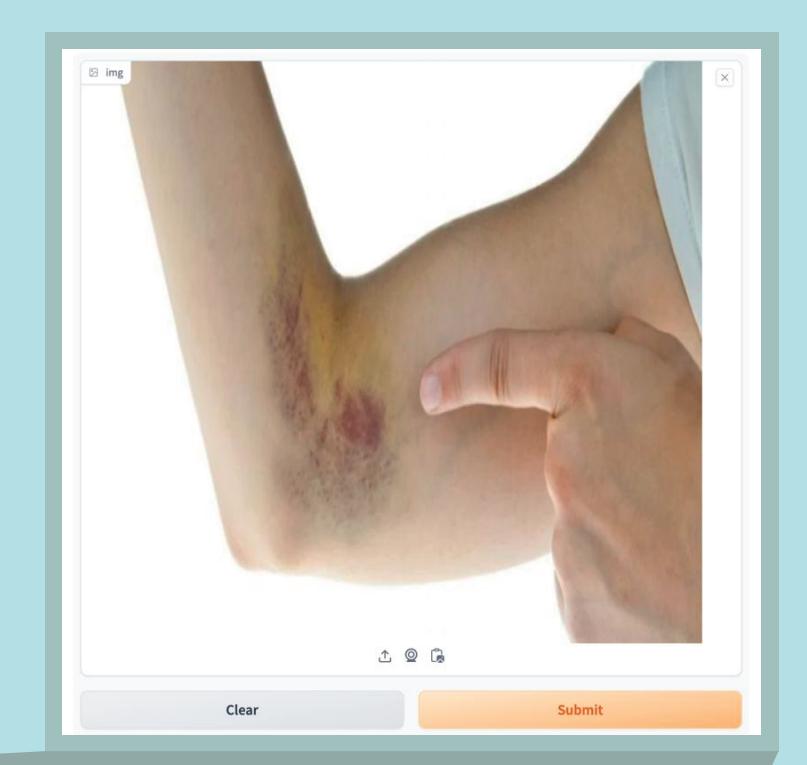


figure6 : Website test

FUTURE WORK

Our future work includes seeking expert labeling of wound images with their corresponding wound properties and then training a regression head on those properties to determine the risk factor for each wound, allowing for better prioritization.

