

## Vision AI for Wound Identification & Recommended Treatment



# Wound Misidentification



**20%**

**Wounds Initially  
misdiagnosed  
by healthcare  
professionals**



**66%**

**chronic wounds  
caused by improper initial  
treatments**



**70%**

**higher rates of  
readmissions  
Due to Incorrect treatments**

## Cost of Misdiagnosis and Mistreatment

- Misdiagnosed wounds account for over **\$2 billion annually** in additional U.S. healthcare spending
- Chronic wounds cost the U.S. healthcare system more than **\$25 billion** per year
- **Longer recovery times:** Delayed treatment increases the risk of infection leading to prolonged hospital stays

# Impact & Benefits



Real-time analysis for quick decision-making.



Reduces human error and ensures consistent assessments



Faster recovery times and reduced complications

# Competitor & Real World











"Ping An Good Doctor already has a platform and a booth in China."

# Train Data and Model

From Kaggle

## Data Explorer

Version 1 (14.78 MB)

- ▼  Wound\_dataset
  - ▶  Abrasions
  - ▶  Bruises
  - ▶  Burns
  - ▶  Cut
  - ▶  Ingrown\_nails
  - ▶  Laceration
  - ▶  Stab\_wound

Total: 2940 Images !!

## Prediction Result

### Classification Report:

precision

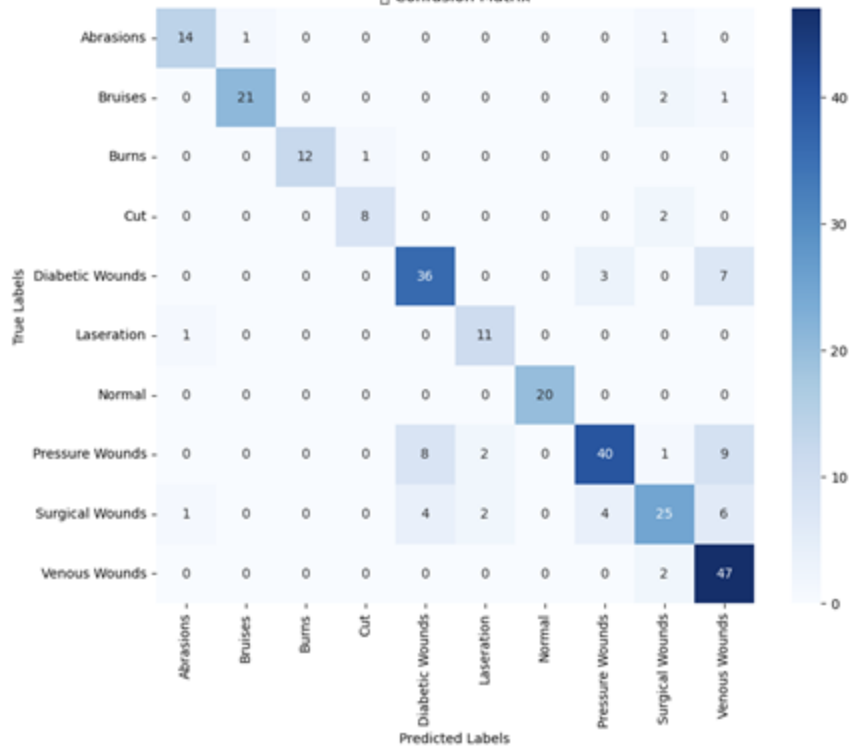
recall

f1-score

support

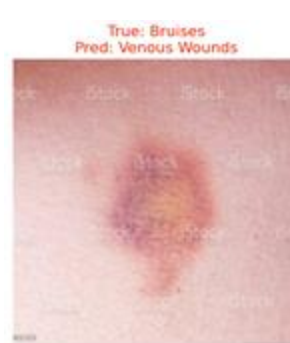
Abrasions	0.88	0.88	0.88	16
Bruises	0.95	0.88	0.91	24
Burns	1.00	0.92	0.96	13
Cut	0.89	0.80	0.84	10
Diabetic Wounds	0.75	0.78	0.77	46
Laceration	0.73	0.92	0.81	12
Normal	1.00	1.00	1.00	20
Pressure Wounds	0.85	0.67	0.75	60
Surgical Wounds	0.76	0.60	0.67	42
Venous Wounds	0.67	0.96	0.79	49
accuracy			0.80	292
macro avg	0.85	0.84	0.84	292
weighted avg	0.81	0.80	0.80	292

### □ Confusion Matrix





# Prediction Result



✗ Total Misclassified Samples: 58



# Vector Embedding & Mongodb Connection

## Step-1

### Image Preprocessing and Feature Extraction:

- Resize to **224x224** pixels to match the input size of ResNet50.
- Normalize the image
- **ResNet50** model (without the top classification layer).
- Extract a **2048-dimensional feature vector** (embedding) that represents high-level features of the image.

## Step 2

### Saving the Embeddings and Metadata:

- Generate Embeddings
- Store Metadata:
  - Extract the **label** from the directory structure.
  - Pair the **image name** and **label** with the **embedding** vector.
- Save to JSON

## Step 3

- Push Data to MongoDB

```
Total image records: 292
```

```
Image: abrasions (1).jpg
```

```
Label: Abrasions
```

```
Embedding length: 2048
```

```
Sample values: [0.9696771502494812, 1.4776711
```

```
Image: abrasions (10).jpg
```

```
Label: Abrasions
```

```
Embedding length: 2048
```

```
Sample values: [1.2132694721221924, 0.9437905
```

# Vector Search Result

QUERY IMAGE: abrasions (1).jpg (Class: Abrasions)

SIMILAR IMAGES (Top 5 Results):

RANK	IMAGE NAME	CLASS	SIMILARITY SCORE
1	mirrored_abrasions (1).jpg	Abrasions	0.9901
2	cut (42).jpg	Cut	0.8937
3	mirrored_abrasions (37).jpg	Abrasions	0.8912
4	abrasions (37).jpg	Abrasions	0.8911
5	mirrored_abrasions (22).jpg	Abrasions	0.8890

Correct class matches: 4/5 (80.0%)

Top match class: Abrasions (Correct)



## **Conclusion:**

- The combination of ResNet50 for classification and Vector Search for storing embeddings enables scalable and efficient wound assessment. This solution ensures fast, accurate classification, aiding quick treatment decisions in critical or remote care settings.

## **Future works:**

- We plan to expand the dataset with images of wounds at different healing stages, allowing healthcare professionals to track recovery progress and improve treatment decisions, leading to better patient outcomes.