Vision AI for Wound Identification & Recommended Treatment

Wound Misidentification

Wounds Initailly misdiagnosed

by healthcare professionals

chronic wounds

caused by improper initial treatments

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

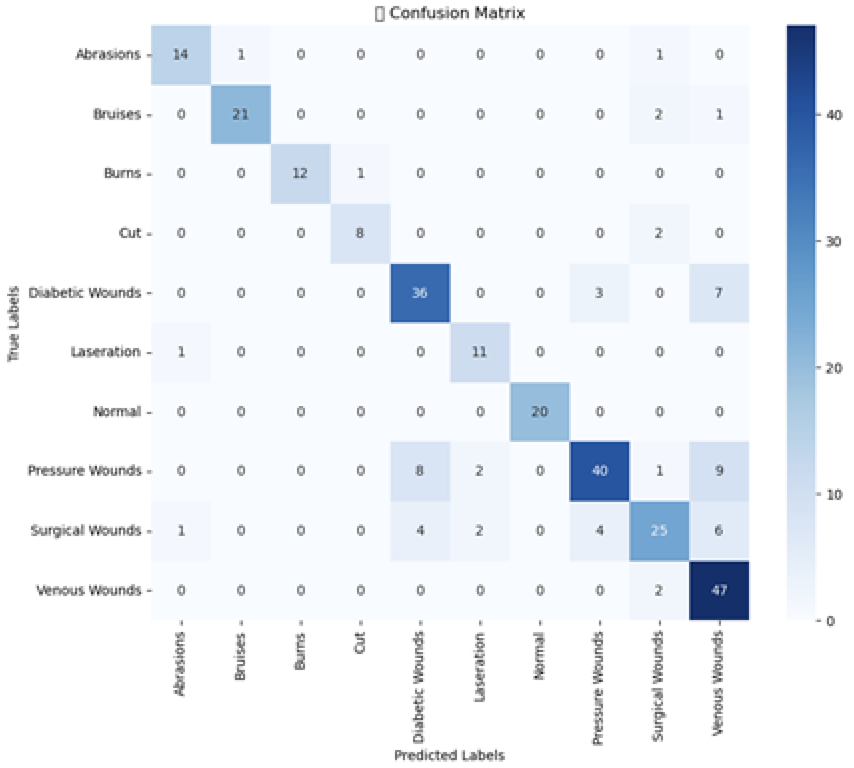
Total: 2940 Images

```
# =========================== #
#     Model Architecture      #
# =========================== #
input_tensor = Input(shape=(img_height, img_width, 3))

x = Conv2D(32, (3, 3), activation="relu")(input_tensor)
x = MaxPooling2D(pool_size=(2, 2))(x)

x = Conv2D(64, (3, 3), activation="relu")(x)
x = MaxPooling2D(pool_size=(2, 2))(x)

x = Conv2D(128, (3, 3), activation="relu")(x)
x = MaxPooling2D(pool_size=(2, 2))(x)

x = Flatten()(x)
feature_vector = Dense(2048, activation="relu", name="feature_output")(x)

class_predictions = Dense(num_classes, activation="softmax", name="class_output")(feature_vector

model = Model(inputs=input_tensor, outputs=[class_predictions, feature_vector])

# =========================== #
#       Model Compile         #
# =========================== #
model.compile(
    optimizer=Adam(learning_rate=0.001),
    loss={"class_output": "categorical_crossentropy", "feature_output": "mean_squared_error"},
    metrics={"class_output": "accuracy"}
)
```

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
Laseration	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



Prediction Result

True: Abrasions
Pred: Bruises

True: Abrasions
Pred: Surgical Wounds

True: Bruises
Pred: Surgical Wounds

True: Bruises
Pred: Venous Wounds

True: Bruises
Pred: Surgical Wounds

True: Burns
Pred: Cut

True: Cut
Pred: Surgical Wounds

True: Cut
Pred: Surgical Wounds

True: Diabetic Wounds
Pred: Venous Wounds

❌ Total Misclassified Samples: 58

Vector Embedding & Mongodb Connection

Step-1

Step 2

Step 3

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.

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

- **Push Data to MongoDB**

```
Total image records: 292

Image: abrasions (1).jpg
Label: Abrasions
Embedding length: 2048
Sample values: [0.9696771502494812, 1.477671

Image: abrasions (10).jpg
Label: Abrasions
Embedding length: 2048
Sample values: [1.2132694721221924, 0.943790
```

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)

Query: abrasions (1).jpg
Class: Abrasions

Top Match: mirrored_abrasions (1).jpg
Class: Abrasions
Score: 0.9901

Conclusion:

- The combination of CNN 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.