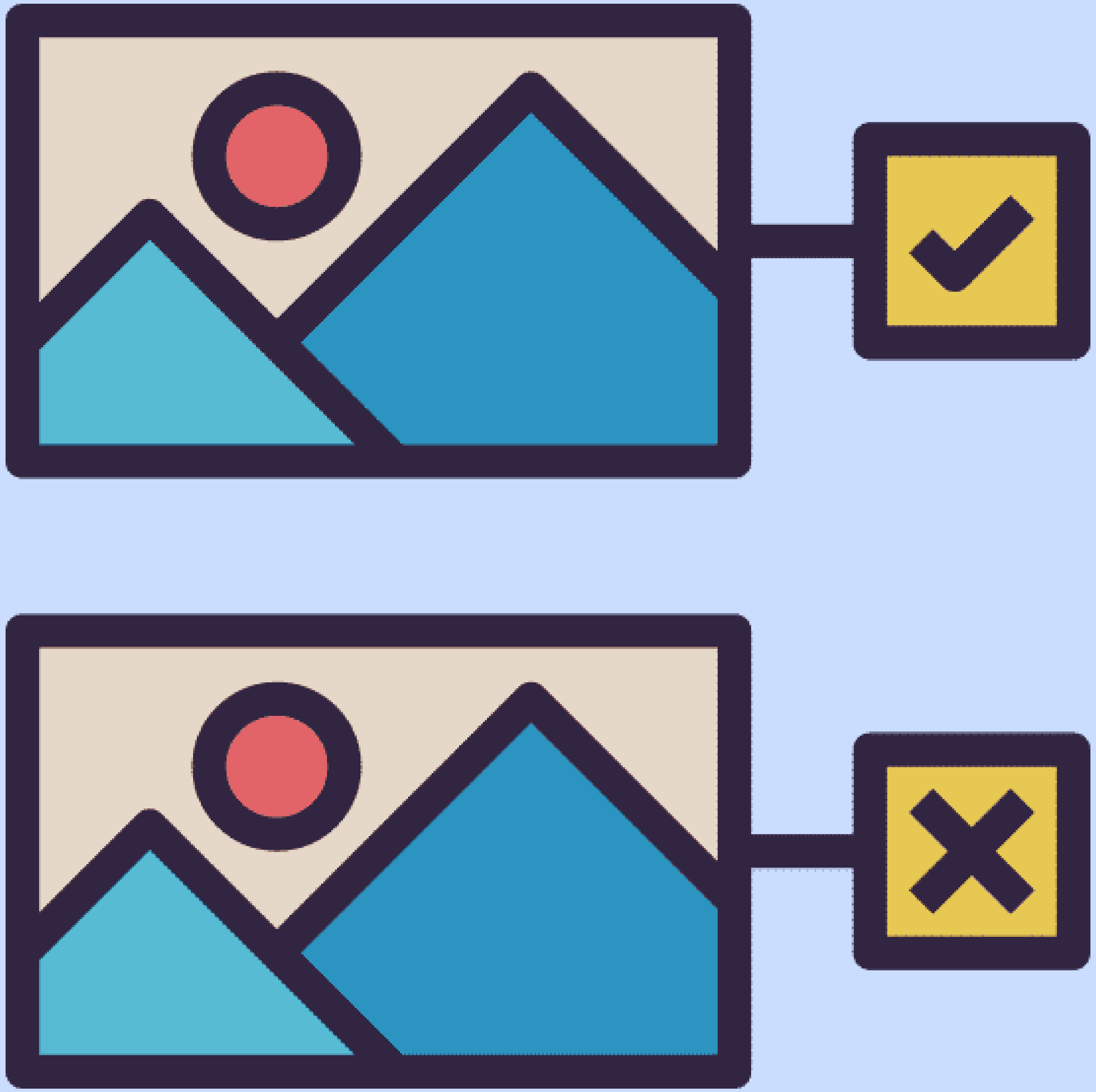


DETECTING FRAUDULENT RETURNS DUE TO FAKE AI GEN-IMAGES IN E-COMMERCE

REAL VS FAKE

TEAM MEMBERS

1. Rishav Rana
2. Vivek Kumar Manjhi
3. Roshan Kumar
4. Kartik Sinha
5. Rakesh Kumar
6. Satya Ranjan Rout

INTRODUCTION

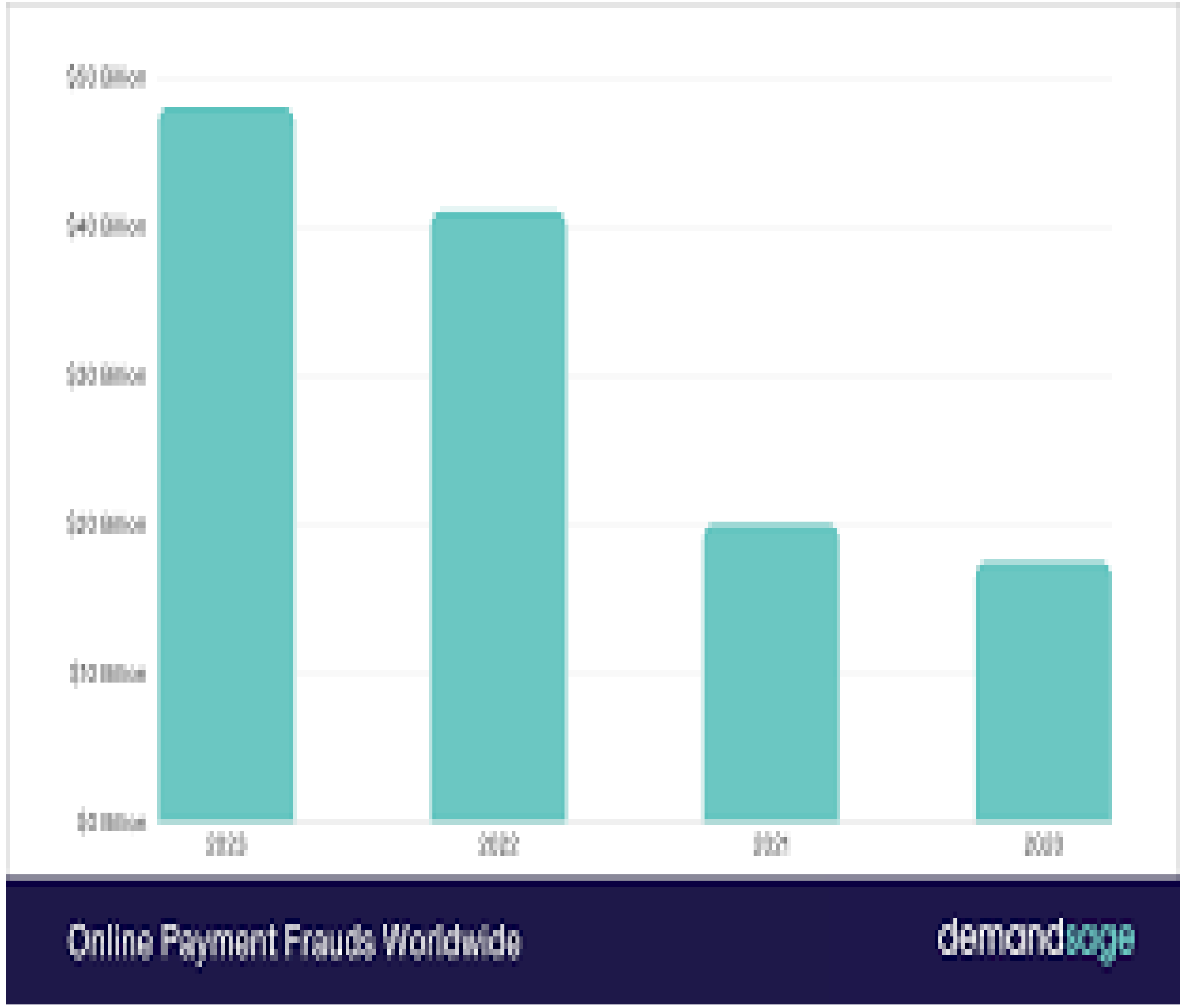
- The rise of e-commerce has made shopping more convenient with flexible return options, but it has also led to an increase in return fraud.

- Advancements in generative AI and image editing tools have made it easier to create fake return evidence, making it difficult for traditional validation systems to detect subtle fraud.

PROJECT MOTIVATION

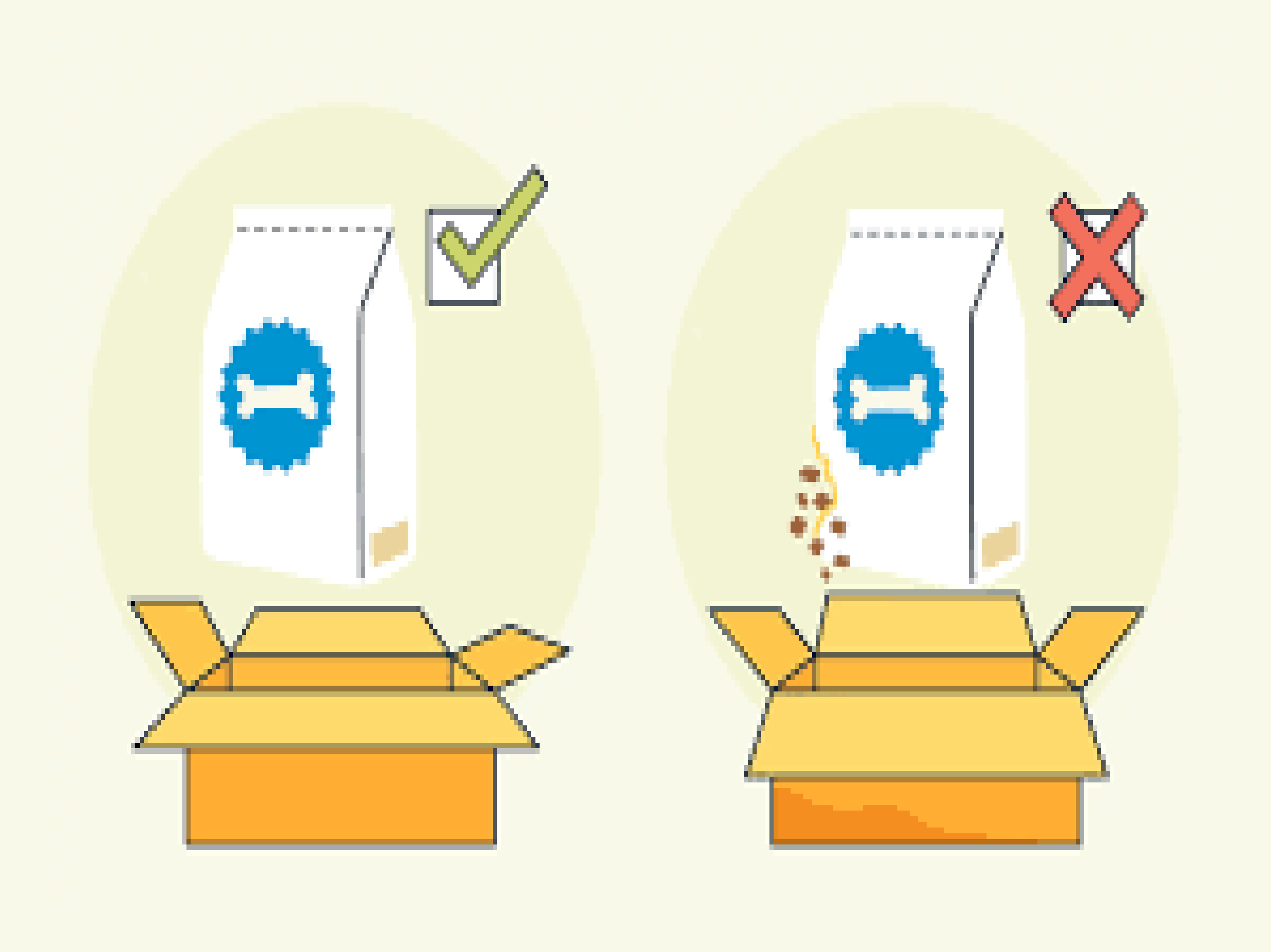
- With rising trend of fraudulent returns, especially those involving fake damaged images and AI-generated content has motivated us for this project. Over the year E-commerce platforms are facing an increase in scams, with customers exploiting return policies by submitting false evidence..

- This growing fraud leads to financial losses, operational disruptions, and damaged brand trust, while burdening honest customers.



REAL-LIFE PROBLEMS

- E-commerce platforms face growing issues with fraudulent returns, where customers submit fake damage claims or AI-generated evidence.
- Hard to distinguish real vs fake damage or AI content.
- AI tools make it easier to manipulate evidence.
- Fake returns create massive financial loss.

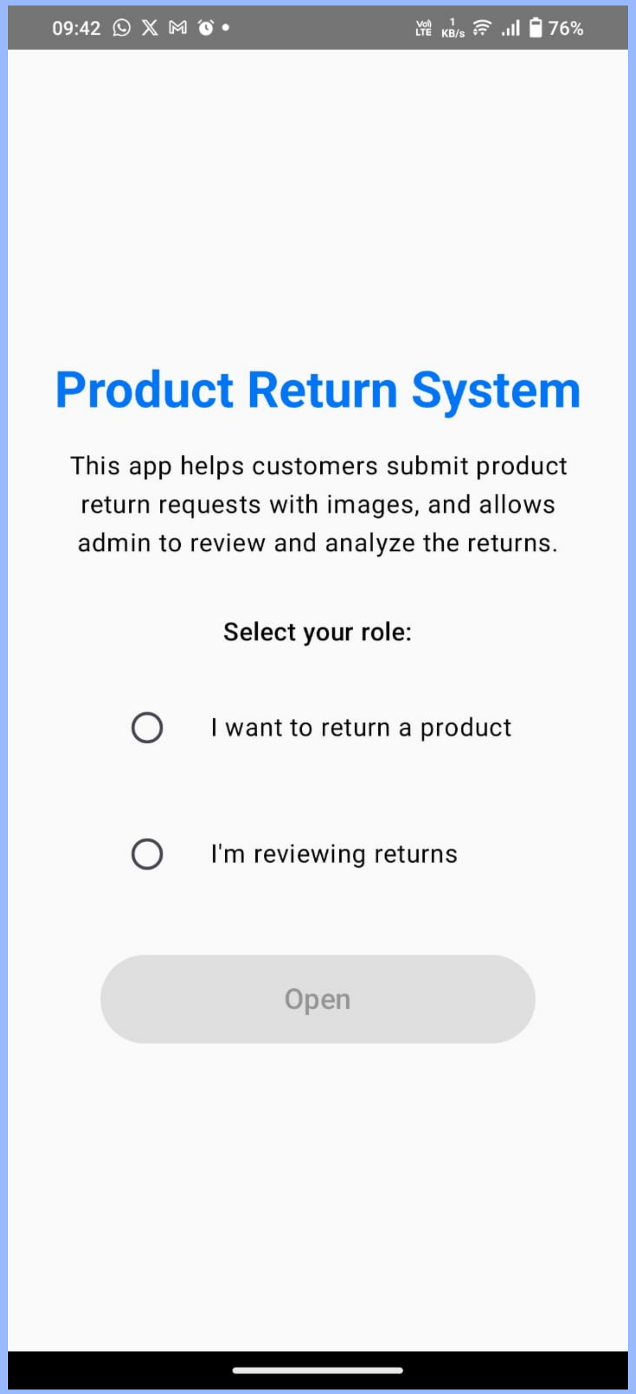


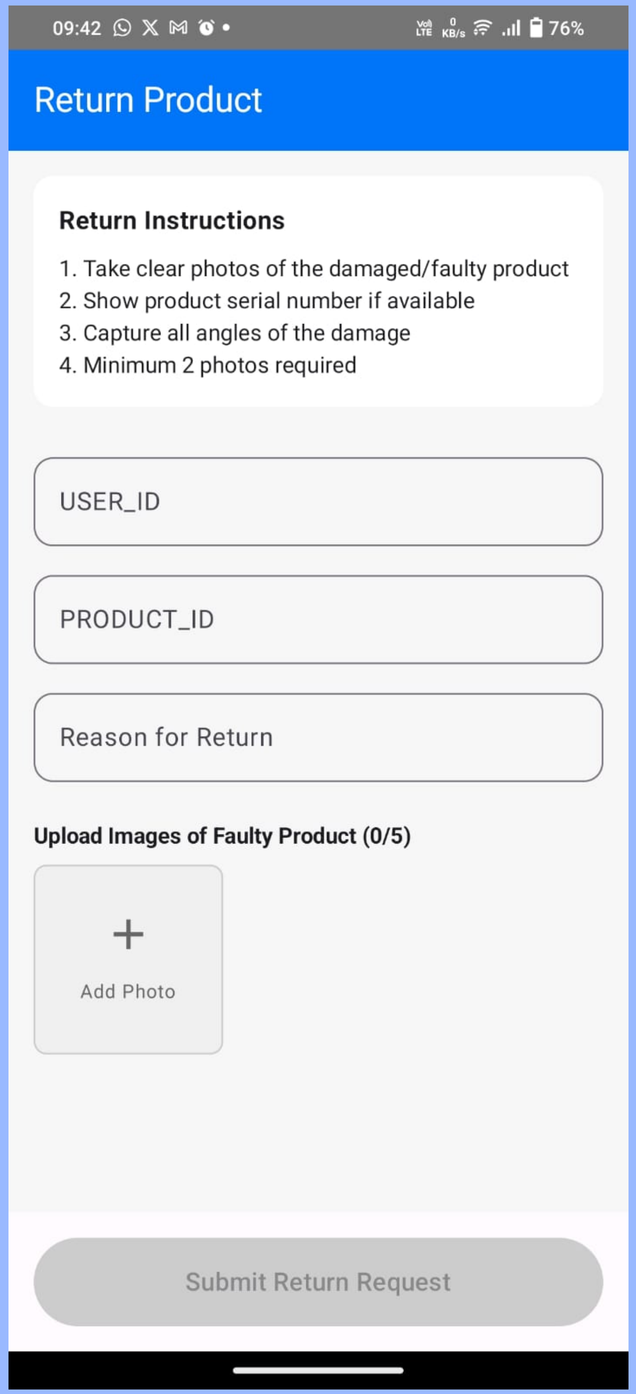
TECHNOLOGY USED

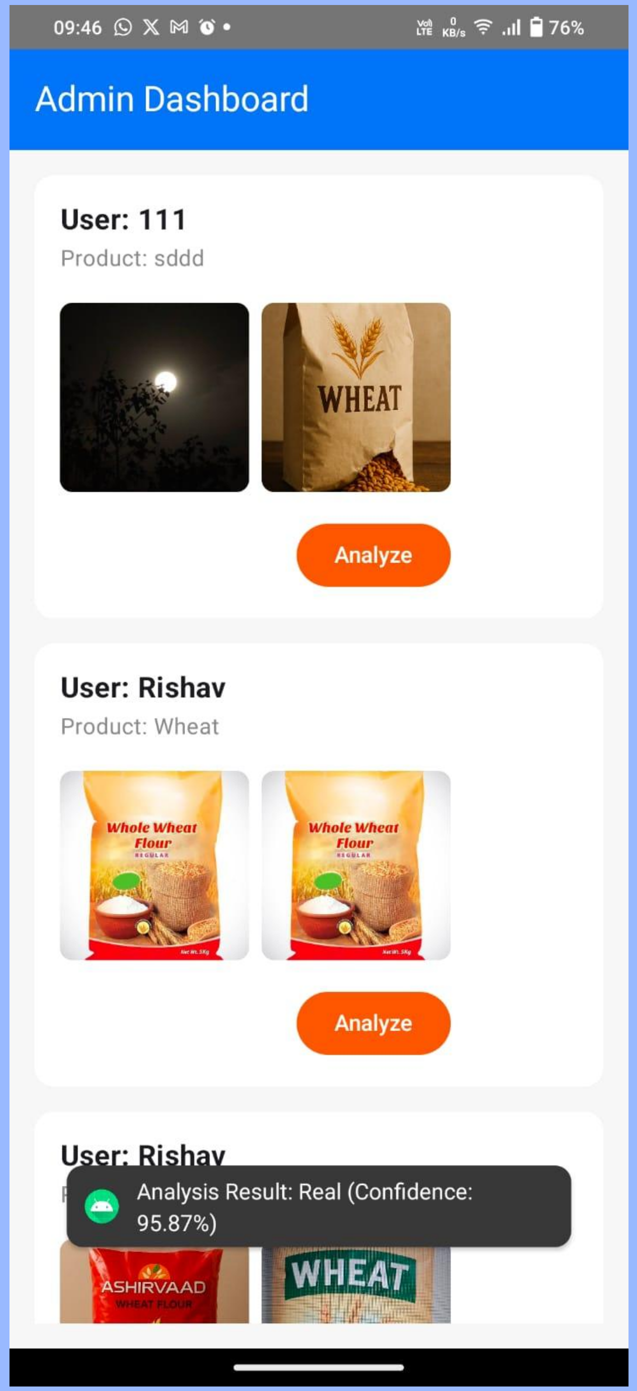
MODEL

- ➢ **PYTHON Libraries**
  - TensorFlow/Keras
  - Streamlit
  - NumPy
  - Pillow
- ➢ **EfficientNet for image classification**
- ➢ **AI image detection libraries**
- ➢ **Data visualization (Matplotlib)**

APP IMPLEMENTATION







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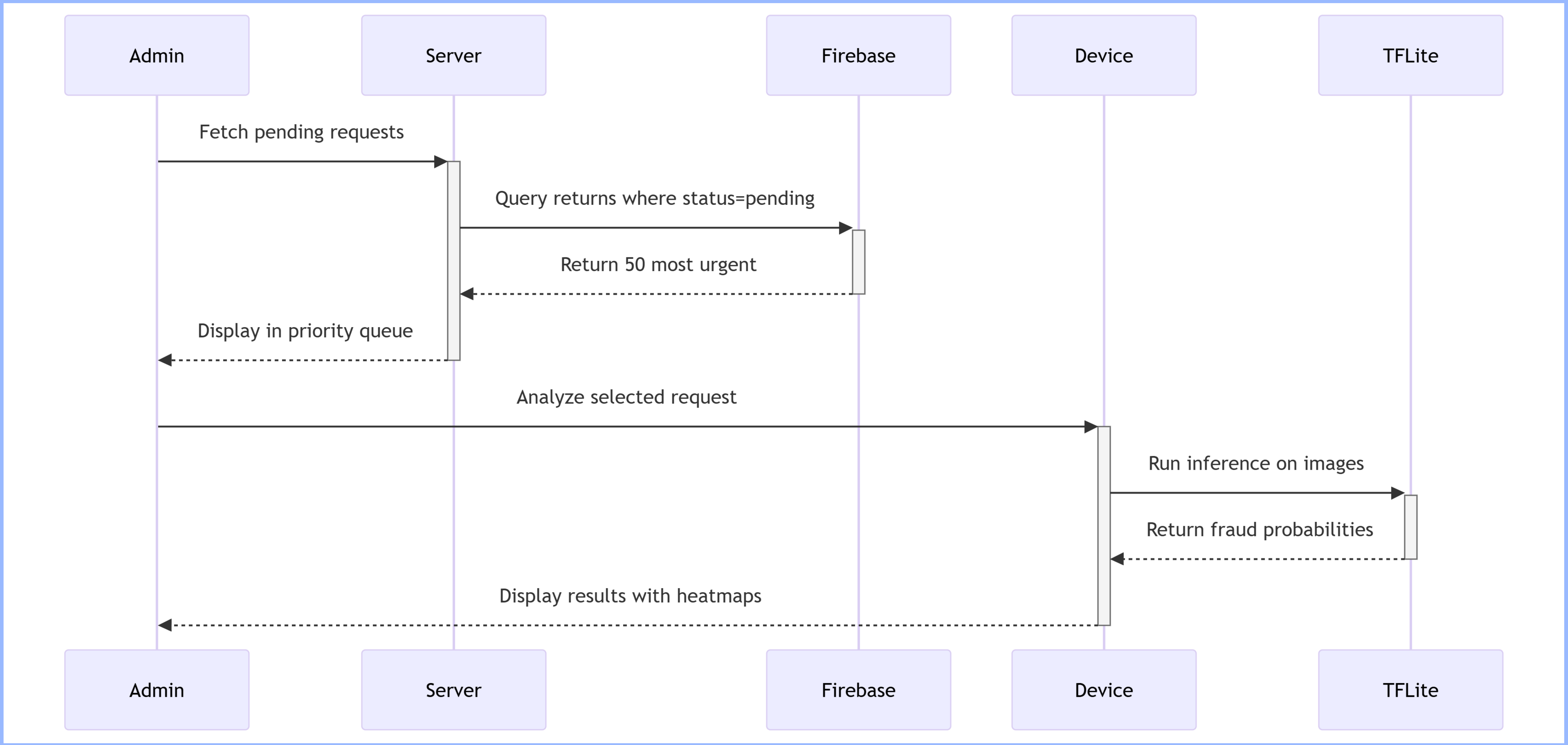


DATASET USED

A curated dataset containing both real and AI-generated images.

https://www.kaggle.com/datasets/birdy654/cifake-real-and-ai-generated-synthetic-images

NUMBER OF CLASSES-
2

Training Set:

- 50,000 real images
- 50,000 AI-generated images

Testing Set:

- 10,000 real images
- 10,000 AI-generated images

CIFAKE Dataset

METHODOLOGY

IMAGE PREPROCESSING

- Resize → 32 × 32 px
- Efficient Net-specific normalization
- Pixel scaling to [0 – 1]

FEATURE EXTRACTION

- EfficientNet-B0 without top (pre-trained weights, last 18 layers unfrozen)

CUSTOM LAYER

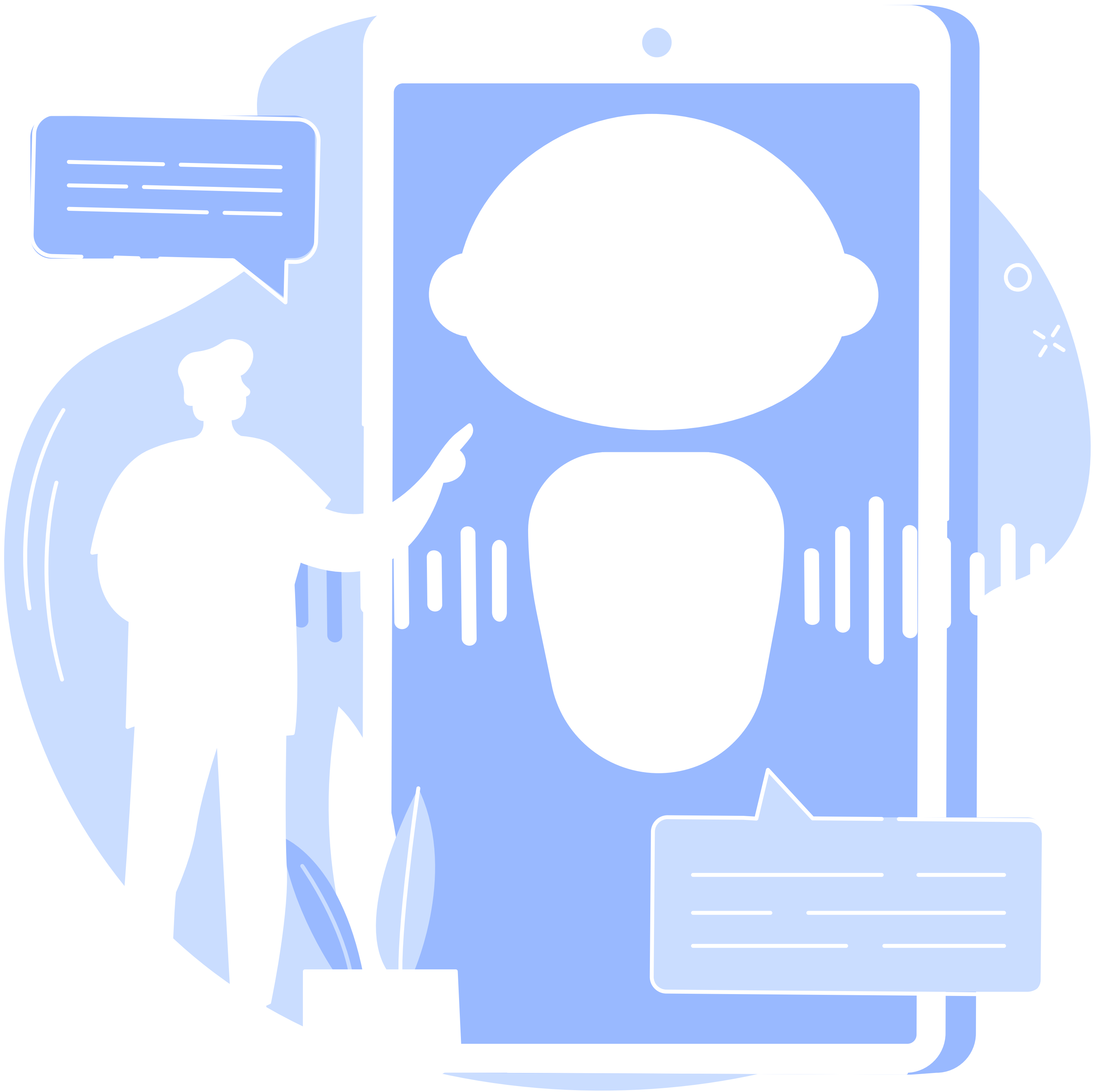
- Dense 256 + ReLU
- Dropout 0.5
- 2 Softmax neurons

EVALUATI ON

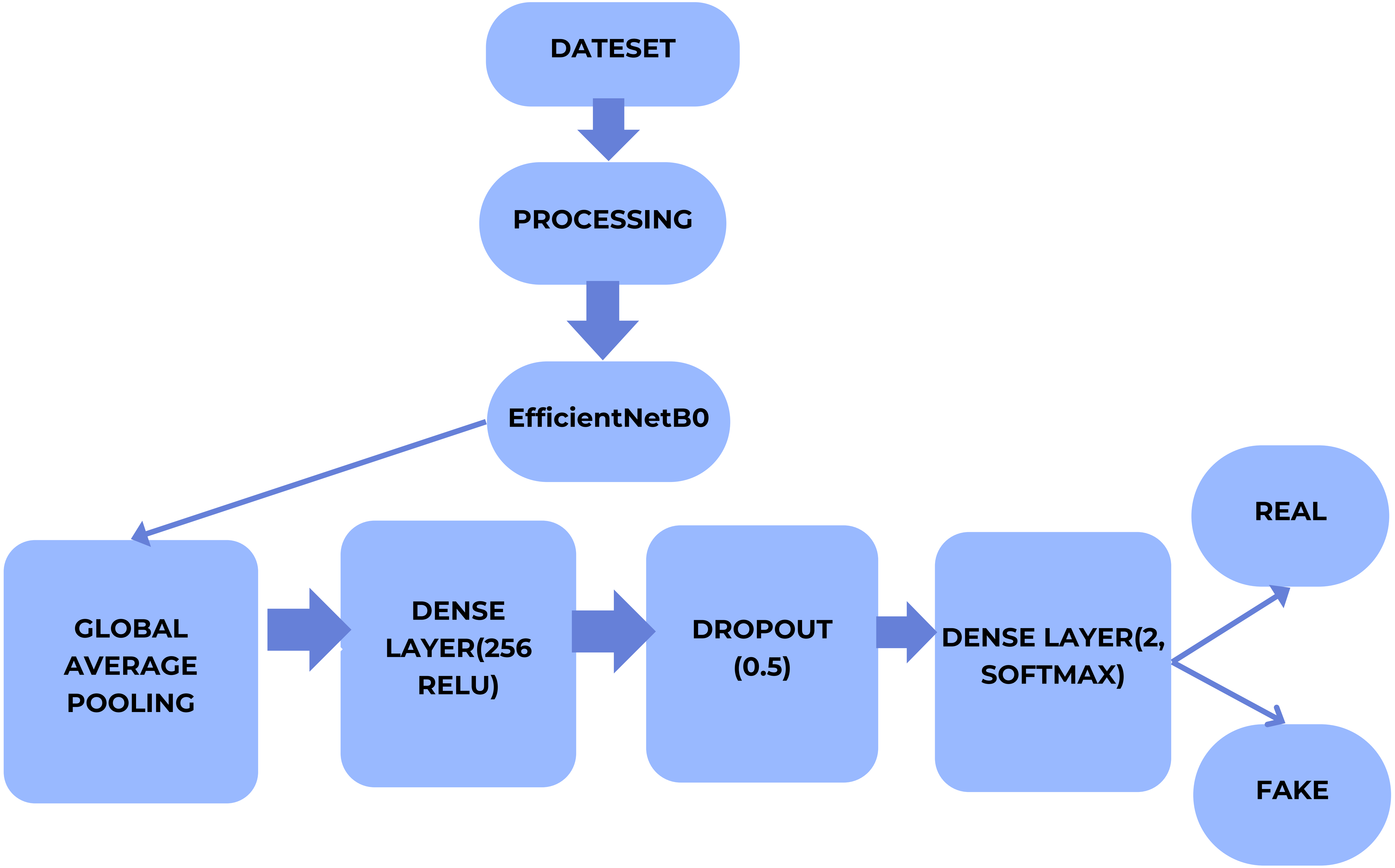
- Precision
- Recall
- F1-Score
- Accuracy

MODEL ARCHITECTURE

- Unfroze top 18 layers for fine-tuning
- Preprocessing: **efficientnet.preprocess_input**
- Architecture:
- **GlobalAveragePooling2D →** converts features to 1D
- **Dense(256, relu) + Dropout(0.5) →** learns deep patterns and prevents overfitting
- **Dense(2, softmax) →** final classification layer



MODEL ARCHITECTURE



TRAINING CONFIGURATION

Optimization Techniques:

- Stochastic Gradient Descent (SGD)
- Learning rate: 0.001
- Momentum: 0.9

Evaluation Metrics:

- Accuracy
- Precision
- Recall
- F1 Score
- AUC

Loss Function:

Binary Crossentropy

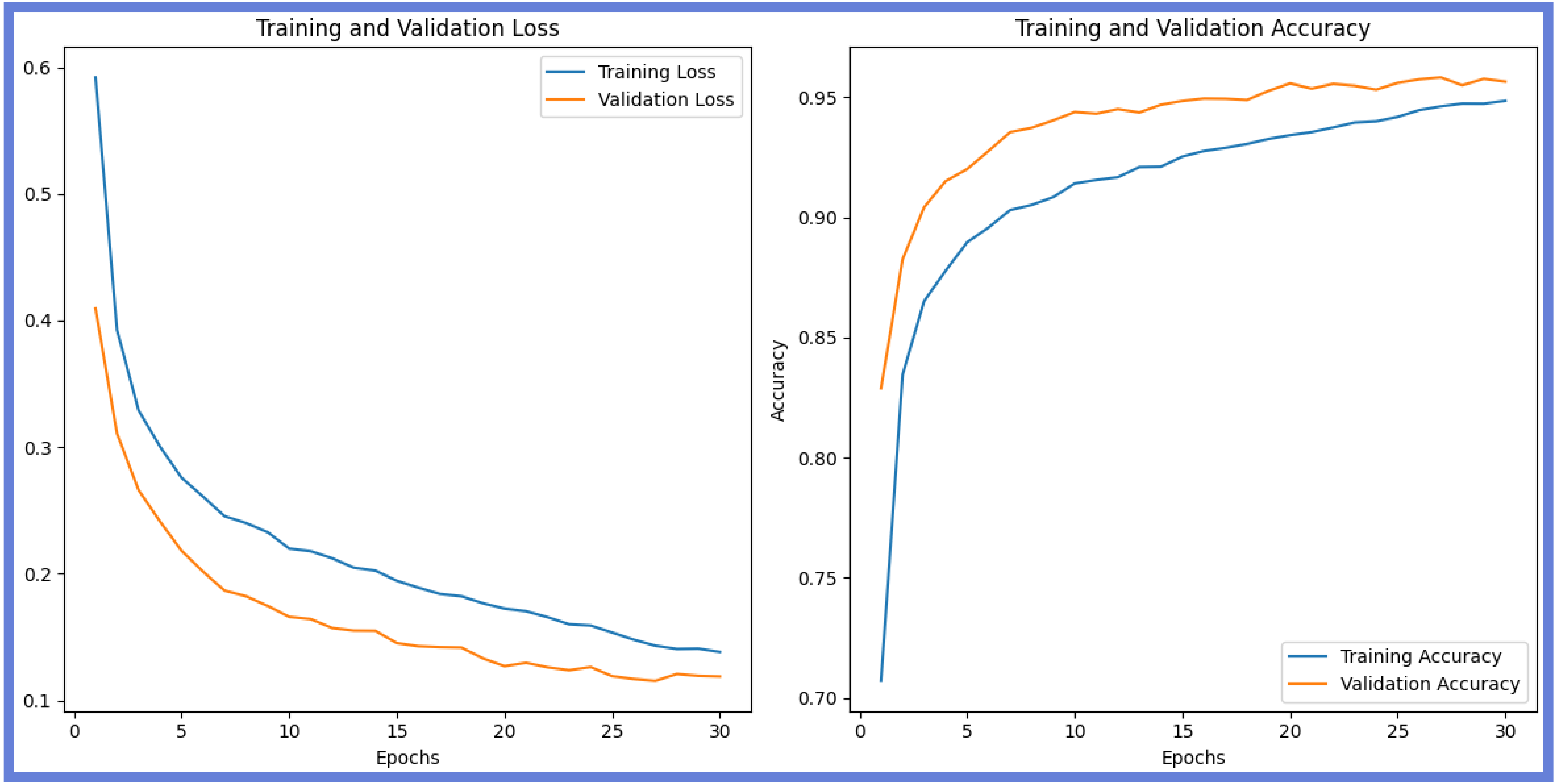
Epochs: 30

Batch Size: 16

RESULTS

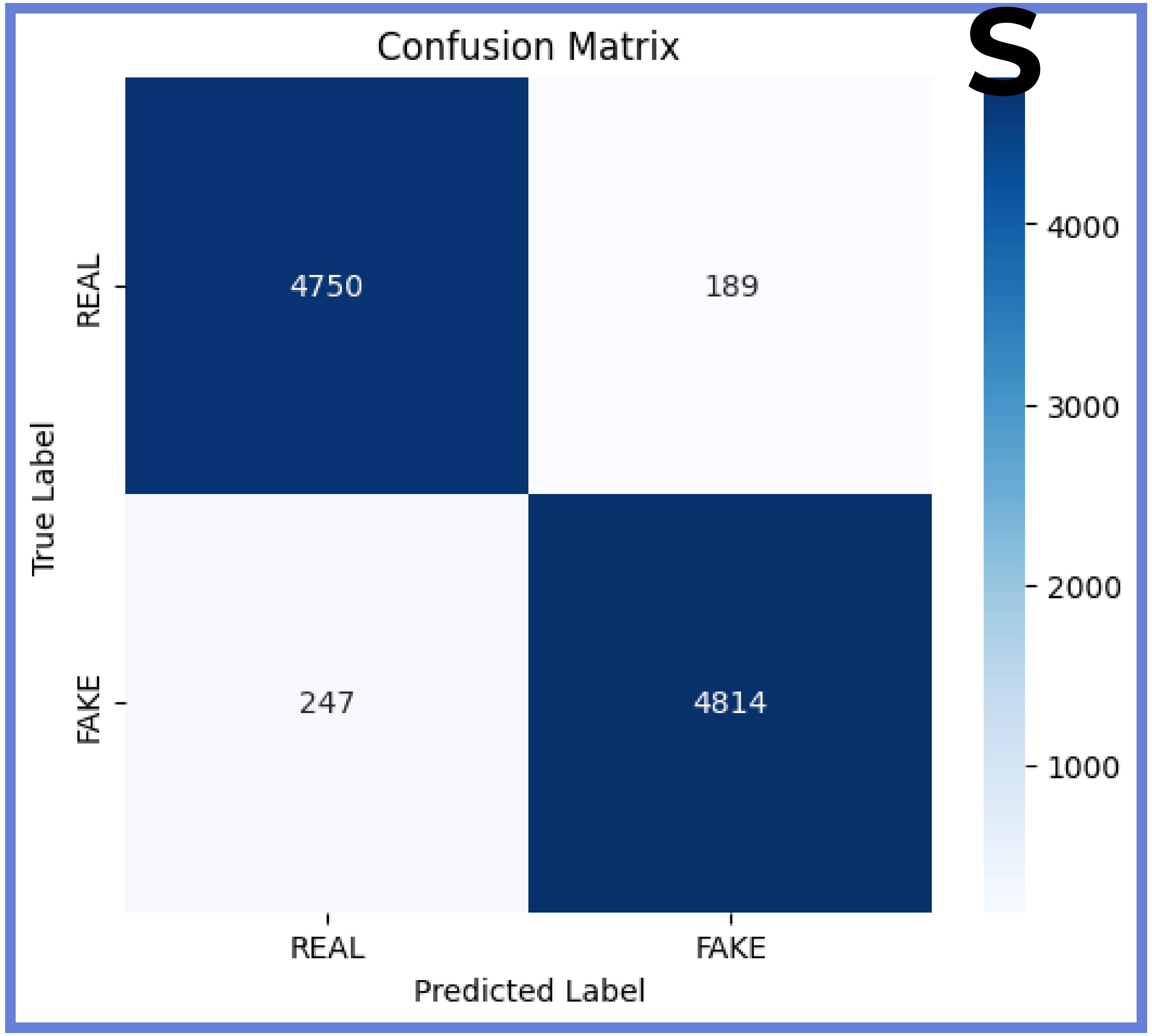
Metric	Real	Fake	Overall
Precision	96%	95%	96%
Recall	95%	96%	96%
F1-Score	96%	96%	96.8%
Accuracy	96%		

RESULTS



Training and Validation Loss
Training Loss
Validation Loss
0.6
0.5
0.4
0.3
0.2
0.1
0
5
10
15
20
25
30
Epochs
Training and Validation Accuracy
Accuracy
0.95
0.90
0.85
0.80
0.75
0.70
Training Accuracy
Validation Accuracy
0
5
10
15
20
25
30
Epochs

RESULTS



True Positives (TP): 4750

False Negatives (FN): 189

False Positives (FP): 247

True Negatives (TN): 4814

FUTURE WORK

Integration with E-commerce Platforms

Build a lightweight tool for warehouse teams to verify returns instantly via mobile.

Extend the solution to video-based AI content detection

Integrate into real-time applications .

CONCLUSION

- The model effectively distinguishes between real and AI-generated images.
- Achieved high accuracy and balanced performance on all metrics.
- Demonstrates the power of transfer learning and fine-tuning using modern CNN architectures like EfficientNet.

THANK YOU FOR LISTENING!