A Machine Learning-Based Framework for Early Detection of Trachoma in Resource-Limited Settings

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Abstract

Trachoma, a leading cause of infectious blindness, predominantly affects populations in resource-limited regions worldwide. Early detection and intervention are critical to preventing disease progression and subsequent blindness. This study explores the application of machine learning techniques, including Random Forest, Support Vector Machine (SVM), Convolutional Neural Networks (CNNs), and K-Nearest Neighbors (KNN), for the identification of Trachoma from image datasets. The research methodology encompasses data collection, preprocessing, feature extraction using CNNs, and the training and evaluation of various models. Among these, the SVM model achieved the best performance with 70% accuracy, a precision of 0.68, a recall of 0.69, an F1-score of 0.68, and an ROC AUC of 0.72. These findings highlight the SVM model's effectiveness and its promise as a tool for assisting healthcare professionals in making accurate and timely diagnoses of Trachoma.

Keywords: Trachoma, Random Forest, Support Vector Machine, Convolutional Neural Networks, K-Nearest Neighbors, Detection and Neglected Tropical Diseases.

Introduction

Trachoma, the leading infectious cause of blindness and visual impairment, affects approximately 136 million people across 44 countries. The urgency of the situation is highlighted by the 1.8 million individuals who require surgery to prevent trachomatous blindness (Solomon et al., 2022). Globally, trachoma accounts for 1.2 million cases of blindness and millions of other visual impairments. Over 80% of active trachoma cases are found in Africa, particularly sub-Saharan Africa. In Ethiopia alone, there are 10.2 million reported cases, with the Amhara region accounting for 62.6% of the national burden (WHO, 2023a; WHO, 2023b; Carter Center, 2023).

Clinically, trachoma is caused by the bacterium *Chlamydia trachomatis* and spreads through direct contact with infected eye secretions, contaminated objects like towels, or flies that have come into contact with infected individuals (CDC, 2024). The disease often begins in childhood and, if left untreated, repeated infections can lead to scarring of the inner eyelid, causing the eyelashes to turn inward and damage the cornea—a condition known as trichiasis which may ultimately result in blindness (Mabey et al., 2003). Manual diagnosis through expert grading of ocular images is time-consuming, labour-intensive, and subject to human error, which poses challenges for large-scale screening programs, especially in resource-limited settings.

Recent advancements in machine learning, particularly Convolutional Neural Networks (CNNs), offer a promising solution to improve the efficiency and accuracy of trachoma detection. CNNs have shown success in medical imaging tasks due to their ability to learn and recognize complex visual patterns (Pan, Lan & Xu, 2024; Yamashita et al., 2018). Studies such as Milad et al. (2022) demonstrated that even non-programmers could build accurate AutoML models using labeled conjunctival images. Their models achieved performance comparable to those created by AI specialists, although they noted limitations such as image quality and generalizability. Similarly, Socia et al. (2022) employed ResNet101 and VGG16 architectures to develop CNN-based classifiers that reduced false negatives in diagnosing trachomatous inflammation, achieving a sensitivity of 95% and a positive predictive value between 50–70%. These models also reduced the need for expert review of large image datasets, aligning with findings from McCauley et al. (2019), Ramadhani et al. (2020), and Sisay, Tadesse & Fenta (2021). While promising, these studies emphasized the need for more diverse datasets and further validation for real-world clinical deployment.

Sample images can be found in Figure 1 below:

Fig. 1: Image of Infected eye.

Methodology

In this section, the data collection, data preprocessing, feature extraction, model training and model selection were carefully carried out. Then, the models used in this research are presented.

Data Source and Preparation

This study focuses on detecting trachoma using selected machine learning algorithms. The rationale behind this choice is to evaluate and identify the algorithm that achieves the highest accuracy in trachoma detection. The dataset utilized in this research is sourced from the Trachoma-images dataset available on Figshare. This dataset comprises 1,015 control images without any trachoma symptoms and 614 images of trachoma cases.

Each image in the dataset is labeled according to its diagnostic status, enabling a binary classification framework suitable for supervised learning. The dataset includes varied image conditions, making it valuable for assessing model generalization. To ensure clinical relevance and data quality, images were reviewed to eliminate noise and irrelevant artifacts. The preparation process involved cataloging files, verifying image integrity, and organizing the data into structured directories for seamless automated processing. This step ensured a clean and reliable foundation for subsequent stages, including preprocessing, model training, and evaluation.

Preprocessing Pipeline

To ensure uniformity and enhance model generalization, preprocessing pipeline was implemented. The first step involved data cleaning, where missing images, duplicates, and mislabeled samples were identified and corrected using metadata validation. This step was essential for maintaining data integrity and avoiding skewed model performance.

Next, all images were resized to 224×224 pixels, which aligns with the input size requirements of Convolutional Neural Networks (CNNs) such as VGG16 and ResNet101. Following resizing, normalization was applied by scaling pixel values to a range between 0 and 1. This ensured consistent input distributions and helped stabilize and accelerate the training process.

To further improve the model's robustness and prevent overfitting, data augmentation techniques were employed. These included random rotations, horizontal flips, zooms, and brightness adjustments, which artificially expanded the dataset and exposed the model to more diverse image patterns. The code snippet for data preprossing was presented in Figure 3.

In preparation for classification, the image labels were numerically encoded into binary values, making them compatible with supervised machine learning algorithms. Finally, the dataset was split into three subsets: 70% for training, 20% for validation, and 10% for testing. This split ensured unbiased model evaluation and effective hyperparameter tuning.

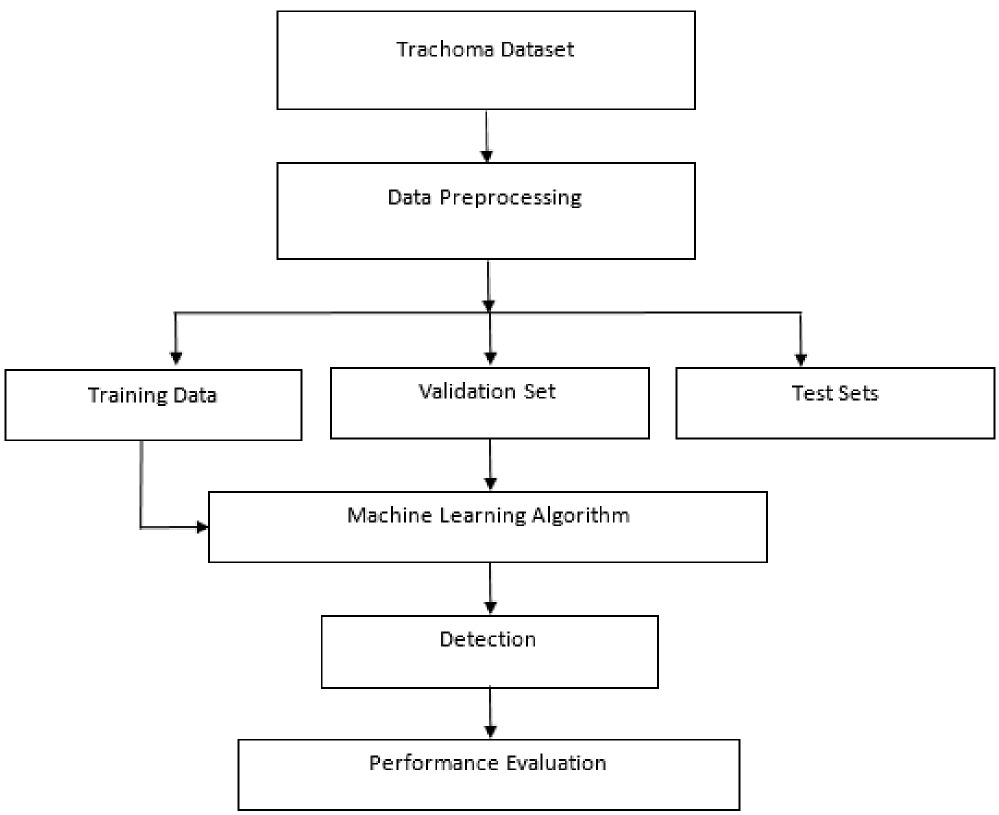

Fig. 2: Framework for the model.

```python
import tensorflow as tf
from tensorflow.keras.preprocessing.image import ImageDataGenerator

# Directory containing the dataset
data_dir = r'C:\Users\Habeeb\Downloads\Finale\dataset'

# ImageDataGenerator for preprocessing and data augmentation
datagen = ImageDataGenerator(
    rescale=1./255,
    validation_split=0.2,
    shear_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True
)
# Training data generator
train_generator = datagen.flow_from_directory(
    data_dir,
    target_size=(224, 224),
    batch_size=32,
    class_mode='binary',
    subset='training'
)
# Validation data generator
validation_generator = datagen.flow_from_directory(
    data_dir,
    target_size=(224, 224),
    batch_size=32,
    class_mode='binary',
    subset='validation'
)
# Test data generator (using validation_split)
test_datagen = ImageDataGenerator(rescale=1./255)
test_generator = test_datagen.flow_from_directory(
    data_dir,
    target_size=(224, 224),
    batch_size=32,
    class_mode='binary',
    subset='validation'  # Reusing validation subset for testing
)
# Data Augmentation for training
train_generator = datagen.flow_from_directory(
    data_dir,
    target_size=(224, 224),
    batch_size=32,
    class_mode='binary',
    subset='training'
)
```

```
Found 1325 images belonging to 2 classes.
```

Fig. 3: Code snippet for data preprocessing.

Model Architectures

The project utilized both advanced deep learning architectures and traditional machine learning algorithms to build a robust trachoma detection system. The deep learning models employed were Convolutional Neural Networks (CNNs), specifically ResNet101 and VGG16, while the traditional models included K-Nearest Neighbors (KNN), Random Forest (RF), and Support Vector Machine (SVM).

ResNet101 and VGG16 were chosen for their proven performance in complex image classification tasks. ResNet101, with its 101 layers and skip connections, is capable of learning deep feature representations while mitigating the vanishing gradient problem. VGG16, known for its simplicity and uniform architecture, effectively captures hierarchical visual features critical for distinguishing subtle patterns in trachoma-infected eyes.

The choice of these models was influenced by their ability to extract meaningful features from medical images and handle the classification task with high accuracy. Traditional models were included to evaluate how well classic machine learning algorithms perform when combined with features extracted by CNNs, offering a comparative perspective between deep learning and traditional approaches.

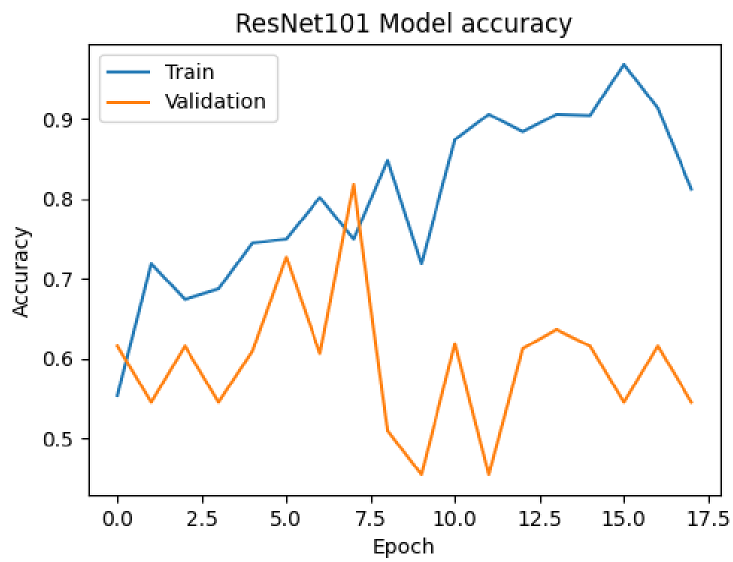

Fig. 4: ResNet101 Model accuracy.

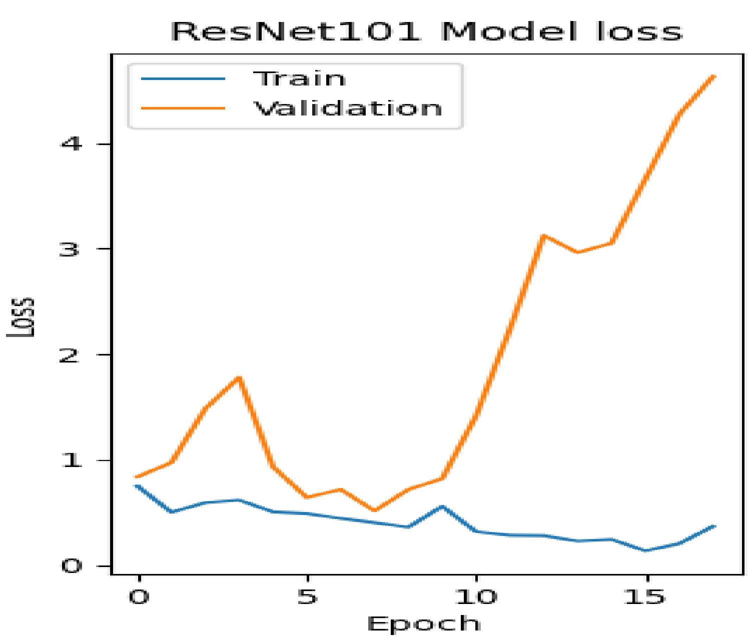

Fig. 5: ResNet101 Model loss.

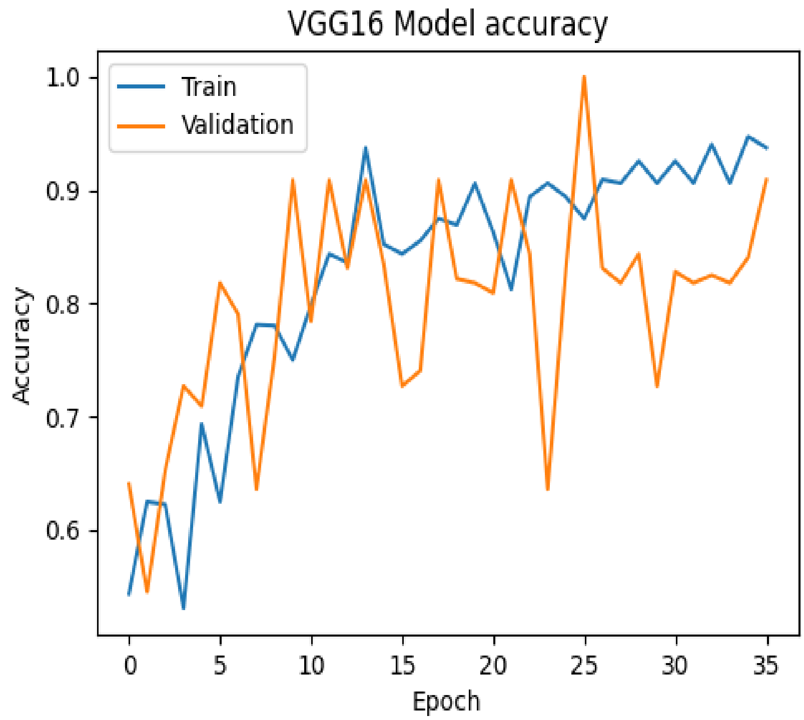

Fig. 6: VGG16 Model accuracy.

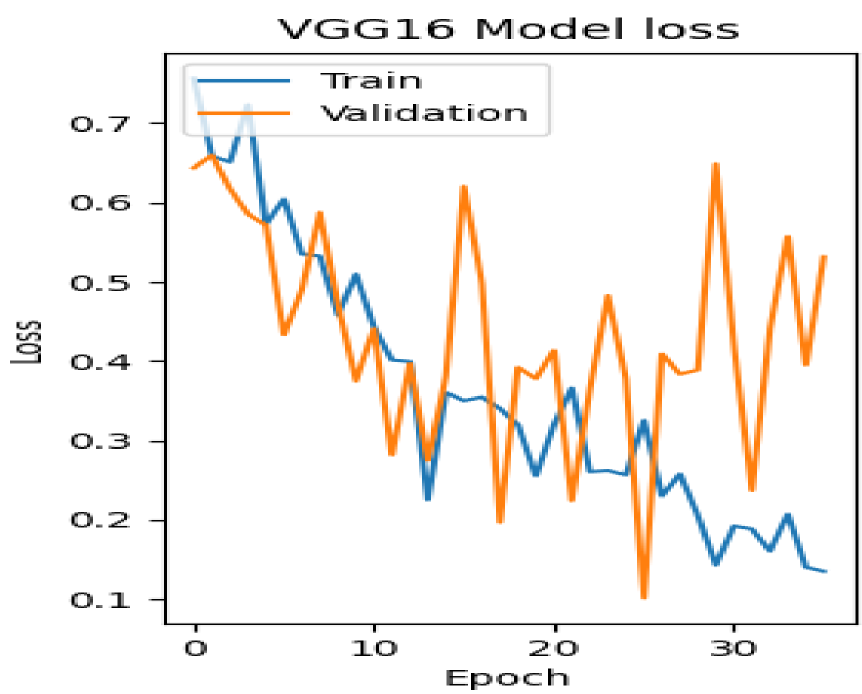

Fig. 7: VGG16 Model loss.

Result

To evaluate the effectiveness of each model, we assessed five key metrics presented in Table 1: accuracy, precision, recall, F1-score, and ROC-AUC. The results are summarized in the performance table below and with the Figures 4-12:

Table 1: Performance Evaluation of Machine Learning Models for Trachoma Detection

Model	Precision	Recall	F1-Score	Accuracy (%)	ROC-AUC
CNN (ResNet101)	0.61	1	0.76	61	0.5
CNN (VGG16)	0.65	0.67	0.66	58	0.46
K-Nearest Neighbors (KNN)	0.51	0.51	0.42	44	0.55
Random Forest (RF)	0.59	0.6	0.59	60	0.68
Support Vector Machine (SVM)	0.68	0.69	0.68	70	0.72

As shown, Support Vector Machine (SVM) outperformed all other models across most metrics, achieving the highest accuracy (70.00%), F1-score (0.68), and ROC-AUC (0.72). This demonstrates its robust classification ability and reliability in distinguishing between trachoma-positive and trachoma-negative cases.

Meanwhile, ResNet101 showed the highest recall (1.00) but lagged in precision (0.61) and ROC-AUC (0.50), indicating a tendency to over-predict positive cases, possibly increasing false positives. Similarly, VGG16 maintained a balanced performance but had slightly lower accuracy.

KNN was the weakest performer, likely due to its inability to capture complex patterns in image data. Random Forest showed strong results overall, especially in ROC-AUC (0.68), suggesting solid predictive capability with a balance of recall and precision.

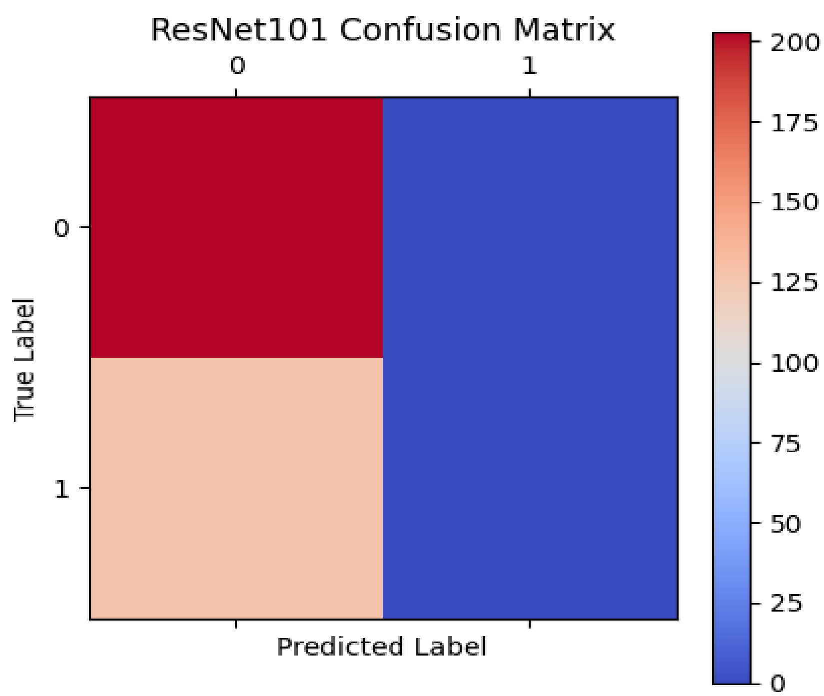

Fig. 8: Confusion matrix for ResNet101.

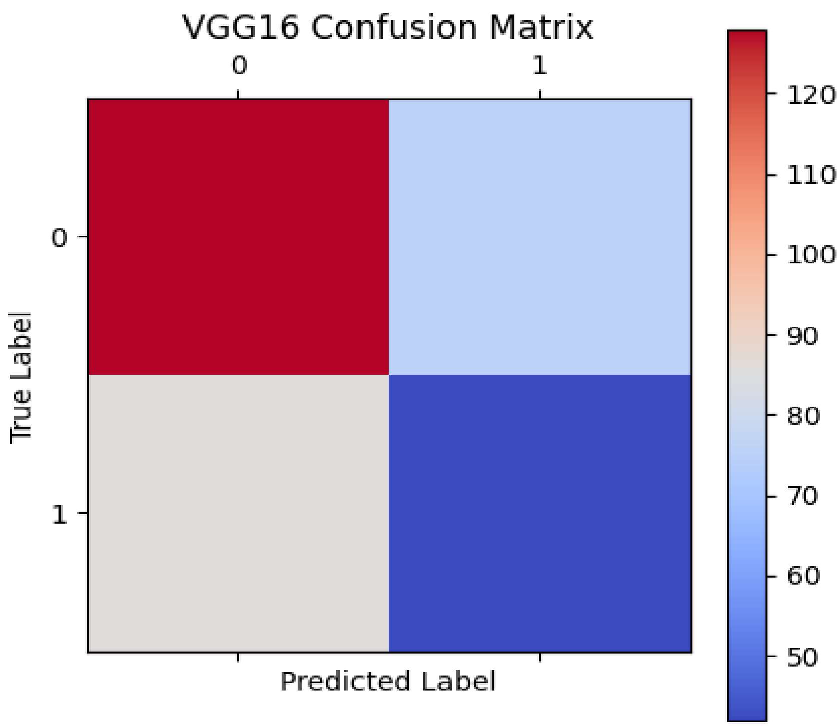

Fig. 9: Confusion matrix forVGG16.

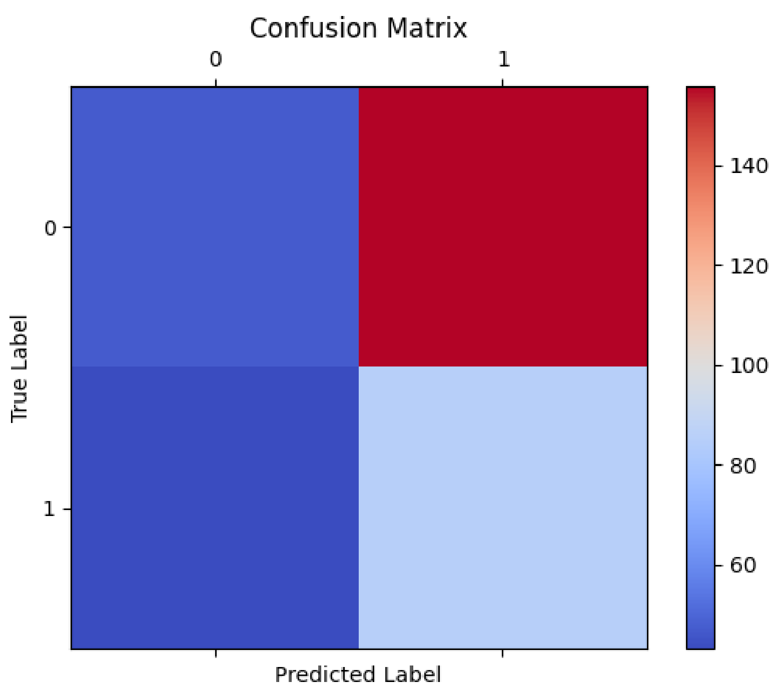

Fig. 10: Confusion matrix for K-Nearest Neighour.

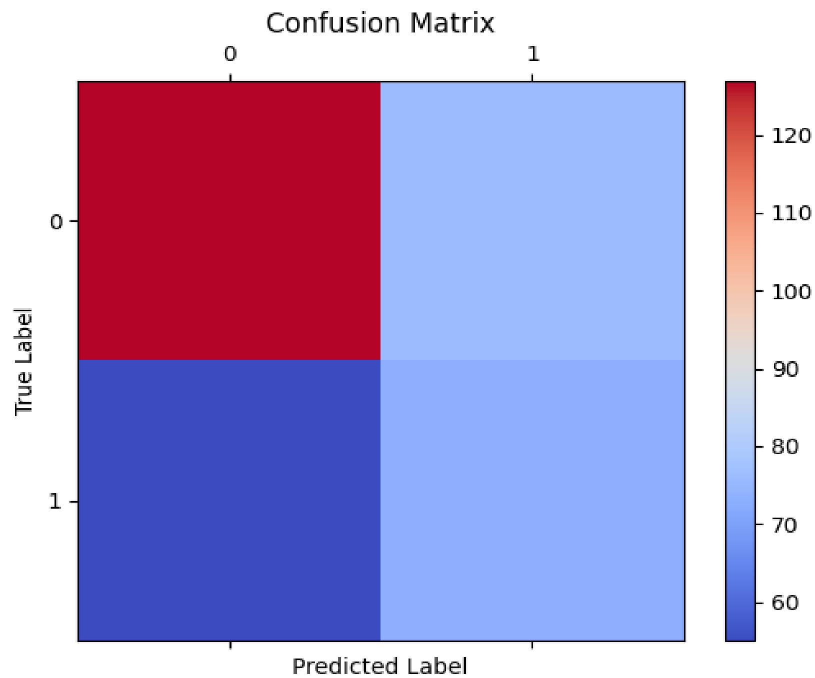

Fig. 11: Confusion matrix for Random Forest.

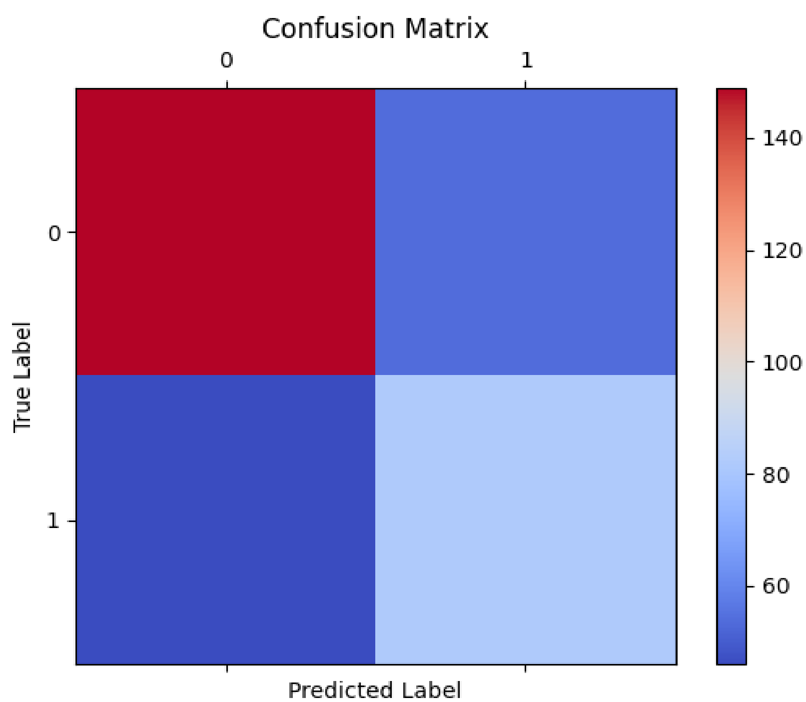

Fig. 12: Confusion matrix for Support Vector Machine

Discussion and Conclusion

This study evaluated different machine learning models for detecting trachoma from eye images. Support Vector Machine (SVM) stood out with the highest accuracy and ROC-AUC score, showing it can perform reliably when paired with well-extracted features. While CNN models like ResNet101 and VGG16 showed strong recall, meaning they were good at identifying positive cases they struggled with precision, suggesting a higher rate of false positives.

Limitation and Real-World Challenges

Despite promising results, the study has several limitations. One key limitation is the relatively small dataset size, which can affect model generalization and robustness. The dataset may not capture sufficient diversity in image quality, lighting conditions, and demographic variation (e.g., across age groups or ethnicities), all of which are critical for real-world deployment. Additionally, since the dataset was curated from a single source, the models may exhibit biases that hinder generalizability when applied to external or more varied data sources.

Another challenge lies in the quality of the input images. In real-world settings, images captured in field conditions might have occlusions, blurs, or background distractions (e.g., gloves, eyelashes, reflections), which could degrade model performance. Although this study attempted to address such issues by evaluating models on Region of Interest (ROI) images, further improvements in preprocessing and artifact removal are necessary.

Conclusion

This study explored the application of machine learning algorithms for the detection of trachoma using image data. Among the models evaluated, the Support Vector Machine (SVM) showed the most consistent and reliable performance across all key metrics: accuracy, precision, recall, and F1-score. These results highlight the SVM model's ability to generalize well from extracted features and make it a suitable candidate for automated trachoma detection tasks.

The findings suggest that with further development, the SVM model could support early diagnosis efforts in clinical and community health settings. Its ability to identify trachoma accurately and efficiently may help healthcare professionals make timely decisions, ultimately reducing the risk of preventable blindness. Future research should focus on expanding the dataset, improving model generalizability, and exploring mobile deployment to make this solution accessible in underserved areas.

Conflict of Interest

On behalf of all authors, the corresponding author states that there is no conflict of interest.

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