University of East London

# ENHANCING RAILWAY SYSTEM MAINTENANCE: AN AI-DRIVEN APPROACH TO IMPROVE THE PREVENTIVE MAINTENANCE OF RAIL TRACKS

**Ayomikun Mosaku**
Engineering | 2024

# OVERVIEW

# ABSTRACT



This research addresses leaf accumulation on railway tracks, a significant cause of train delays, and safety hazards due to reduced wheel-rail adhesion.
The study developed a real-time system capable of identifying leaf accumulation on railway tracks using advanced machine-learning models and computer vision techniques.
Achieved a test accuracy of 99.67% using the VGG19 model, surpassing traditional methods in precision and applicability.
The system can enhance rail safety, reliability, and customer satisfaction.

# INTRODUCTION

Rail travel is the most fuel- and carbon-efficient mode of transport, and it is critical for achieving net zero carbon emissions in Europe.

The UK rail network faces rail delays, train cancellations, and infrastructure issues.

This research addresses leaf accumulation on rail tracks, which causes low adhesion conditions, leading to delays and safety hazards.

**Aim of Study:**

To enhance the reliability and efficiency of the UK rail network by integrating advanced machine learning and computer vision technologies.

Develop a real-time detection system to identify leaf accumulation and enable prompt maintenance actions accurately.

**Objectives**

Design and train a CNN model to recognize and quantify leaf accumulation on railway tracks from visual data.

Implement a real-time monitoring system that integrates the trained model to assess rail track conditions continuously.

Evaluate the accuracy and efficiency of different CNN architectures to select the most effective model for detecting leaf accumulation.

Assess the impact of the real-time detection system on reducing delays, improving train punctuality, and enhancing overall customer satisfaction.

# LITERATURE REVIEW

Network Rail introduced leaf-busting trains in 2019. These trains use high-pressure water jets to remove leaves and apply a sand-steel gel for traction (Network Rail, 2021).

The water-Trak system simulates rainy conditions by applying water to the railhead, improving adhesion, and washing away leaves (Network Rail, 2023).

Both methods have limitations in precision and resource efficiency.
Research Gaps:

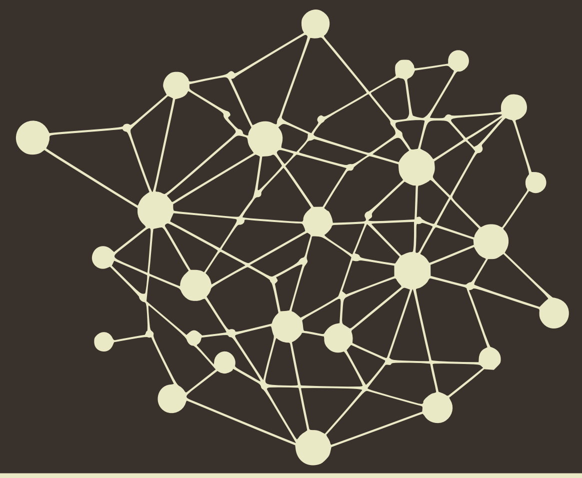
Current methods rely on predictive, weather-based approaches with inherent uncertainties.
A real-time, data-driven solution is needed to detect and accurately address leaf accumulation on rail tracks.

Computer vision offers a direct, technologically advanced method for identifying leaf accumulation.
Provides real-time detection and enables timely maintenance actions.
More accurate and reliable compared to predictive methods based on weather forecasts.
References:

Network Rail. (2021). Leaf-busting trains and their application. Retrieved from Network Rail website.
Network Rail. (2023). Water-Trak system for improving rail adhesion. Retrieved from Network Rail website.
Folorunso, M. O., Watson, M., Martin, A., Whittle, J. W., Sutherland, G., & Lewis, R. (2023). A Machine Learning Approach for Real-Time Wheel-Rail Interface Friction Estimation. Journal of Tribology, 145(9). https://doi.org/10.1115/1.4062373.
Louise, C., & Kirby, H. (2019). Challenges in Railway System Maintenance. Railway Research, 12(3), 123-134.

# THEORY

Convolutional Neural Networks (CNNs) are used for their ability to process grid-like data structures, such as images, by capturing spatial hierarchies of features.



Transfer learning allows pre-trained models to improve the efficiency and accuracy of detecting leaf accumulation, leveraging knowledge from large datasets like ImageNet.

# METHODOLOGY

## 01

Data Collection: Images from primary sources (direct rail track images) and secondary sources (online repositories like Railcam.uk and Google Images).

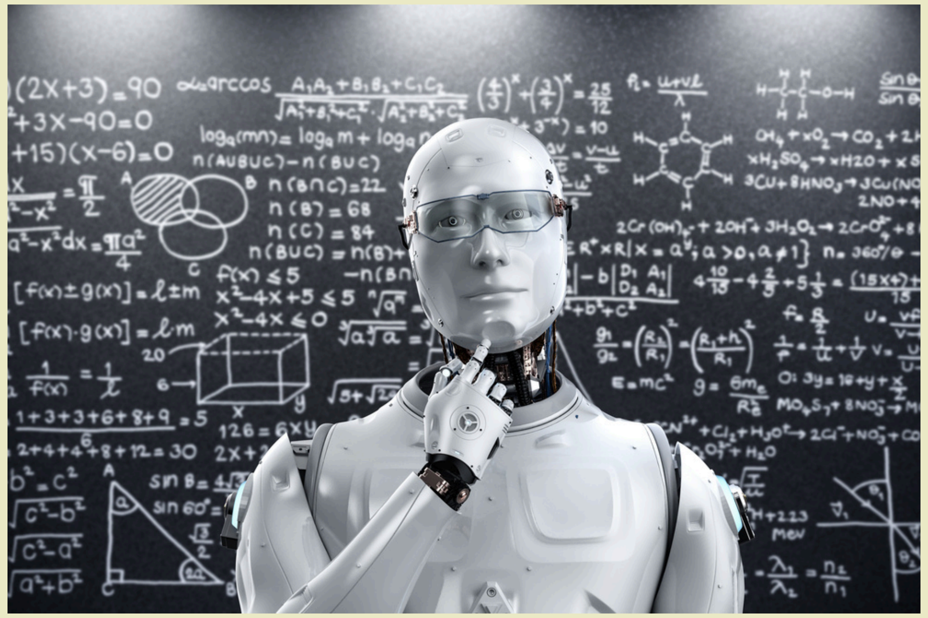
## 02

Preprocessing and Augmentation: Techniques such as resizing, color normalization, and augmentations (e.g., rotations, flips) are applied to enhance the dataset.

Models Used: VGG19, MobileNetV2, ResNet50V2, InceptionV3, Xception, and a custom-built TensorFlow model.

# IMPLEMENTATION

VGG19: High accuracy and simple architecture, suitable for detailed feature extraction.
MobileNetV2: Efficient and lightweight, ideal for mobile and embedded systems deployment.
ResNet50V2: Deep network with residual learning to overcome vanishing gradient problems.
InceptionV3: Uses factorized convolutions to capture multi-scale features.
Xception: Employs depth-wise separable convolutions for high performance with fewer parameters.
Custom Built TensorFlow Model: Tailored for binary classification of leaf accumulation on rail tracks.
Model Implementation:
Models trained using Google Colab for access to high-performance GPUs.
Data split into training (60%), validation (20%), and testing (20%) sets.
Training was conducted over 16 epochs with early stopping based on validation loss to prevent overfitting.

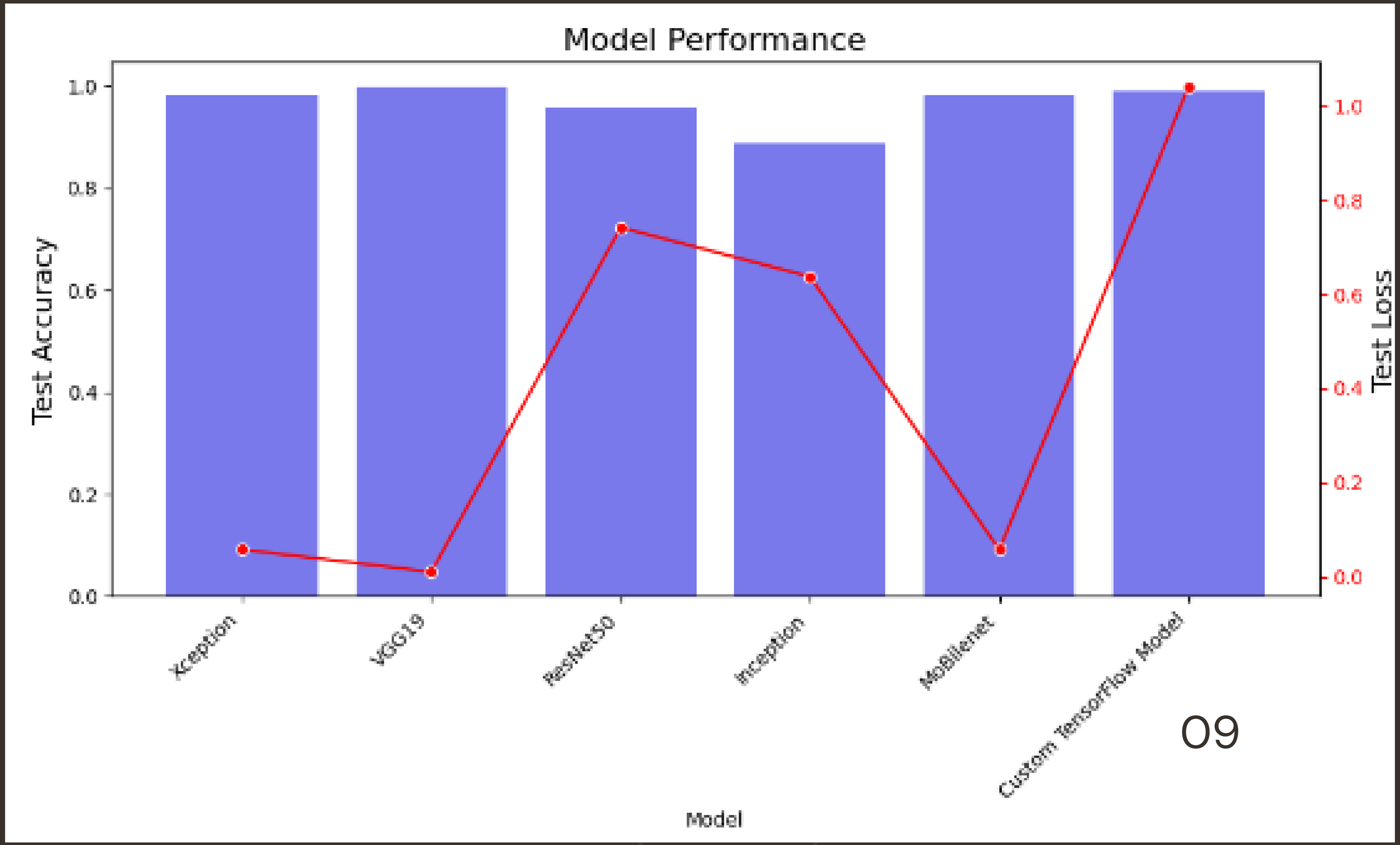


# RESULT

| | Xception | VGG19 | ResNet50 | Inception | MoBilenet | TF |
|---|---|---|---|---|---|---|
| Test Loss | 0.058961 | 0.012111 | 0.711462 | 0.568759 | 0.064665 | 1.036726 |
| Test Accuracy | 0.980263 | 0.996711 | 0.963816 | 0.904605 | 0.973684 | 0.993421 |

VGG19 achieved the highest accuracy of 99.67%, demonstrating superior performance in detecting leaf accumulation.

The Custom TensorFlow model also showed promising results with high accuracy.



# RESULT

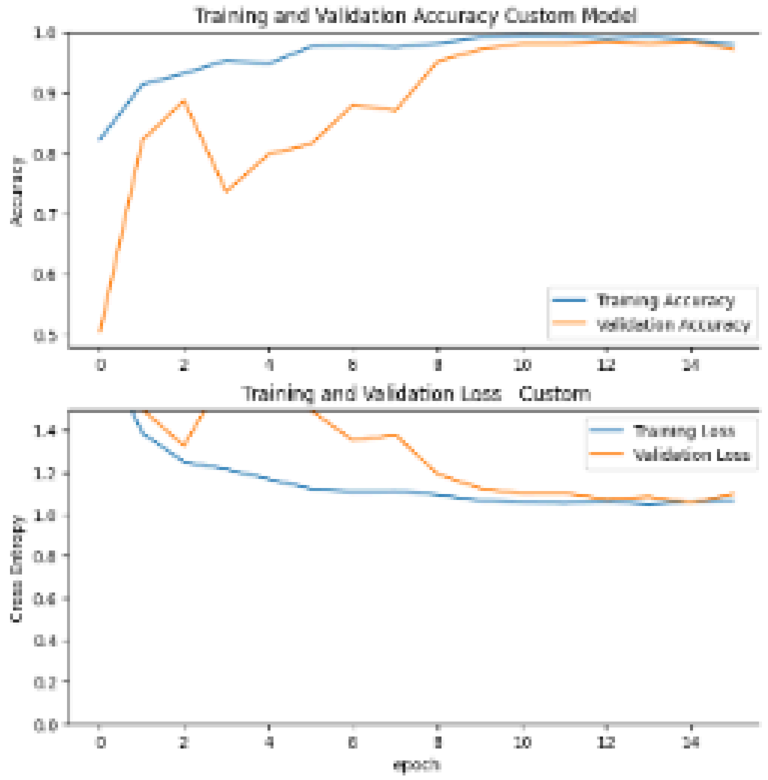



Fig 4.2 Training and Validation Accuracy and Loss Plot for Custom-Built Model


Fig 4.4 Training and Validation Accuracy and Loss Plot for Inception Model

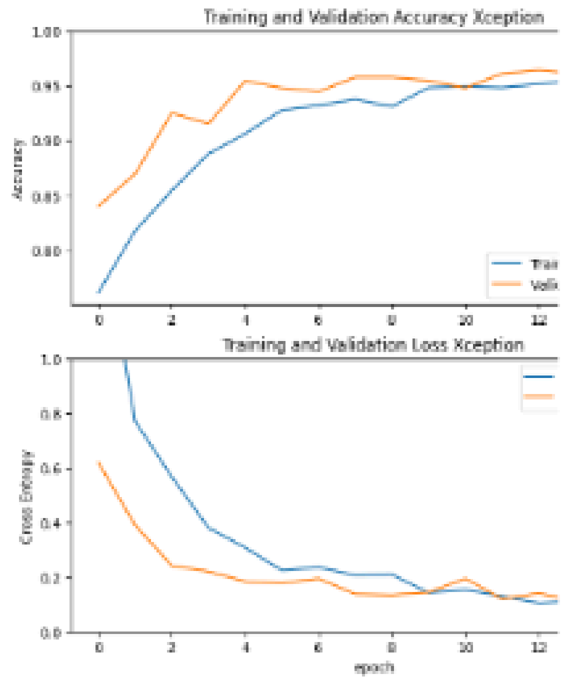



Fig 4.3 Training and Validation Accuracy and Loss Plot for Xception Model

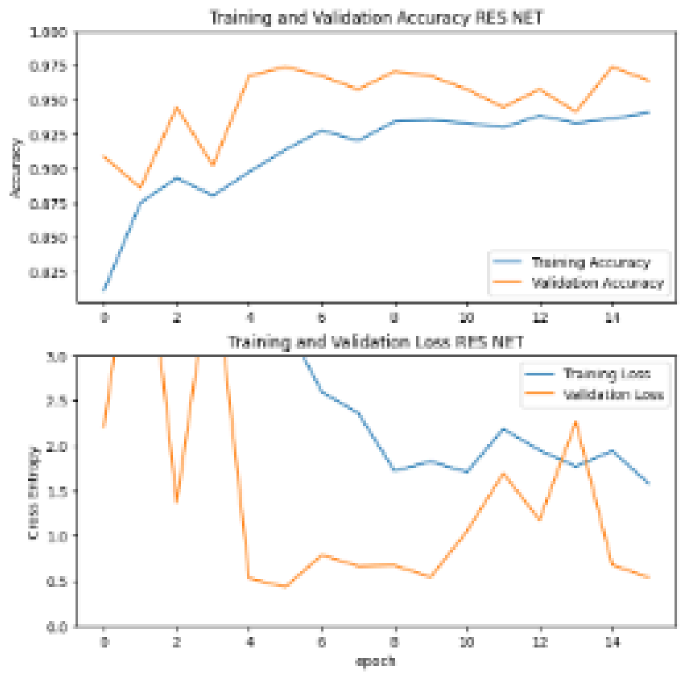



Fig 4.5 Training and Validation Accuracy and Loss Plot for RESNET (Residual Networks) Model


Fig 4.6 Training and Validation Accuracy and Loss Plot for

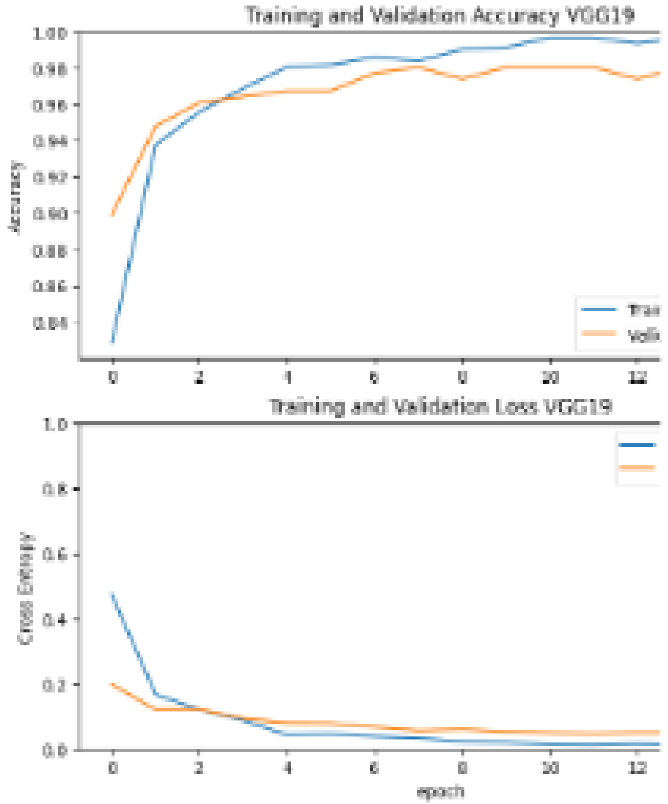
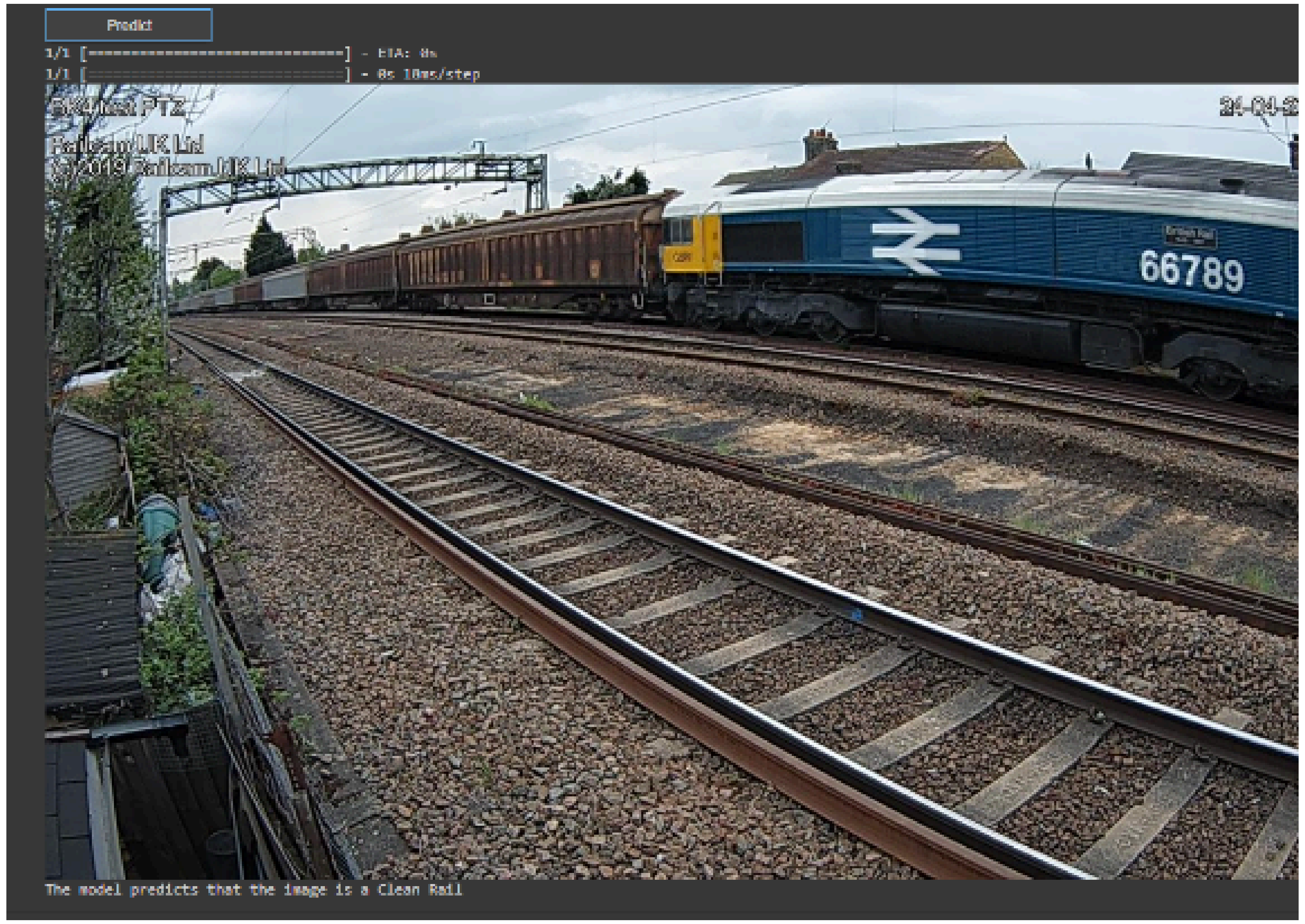


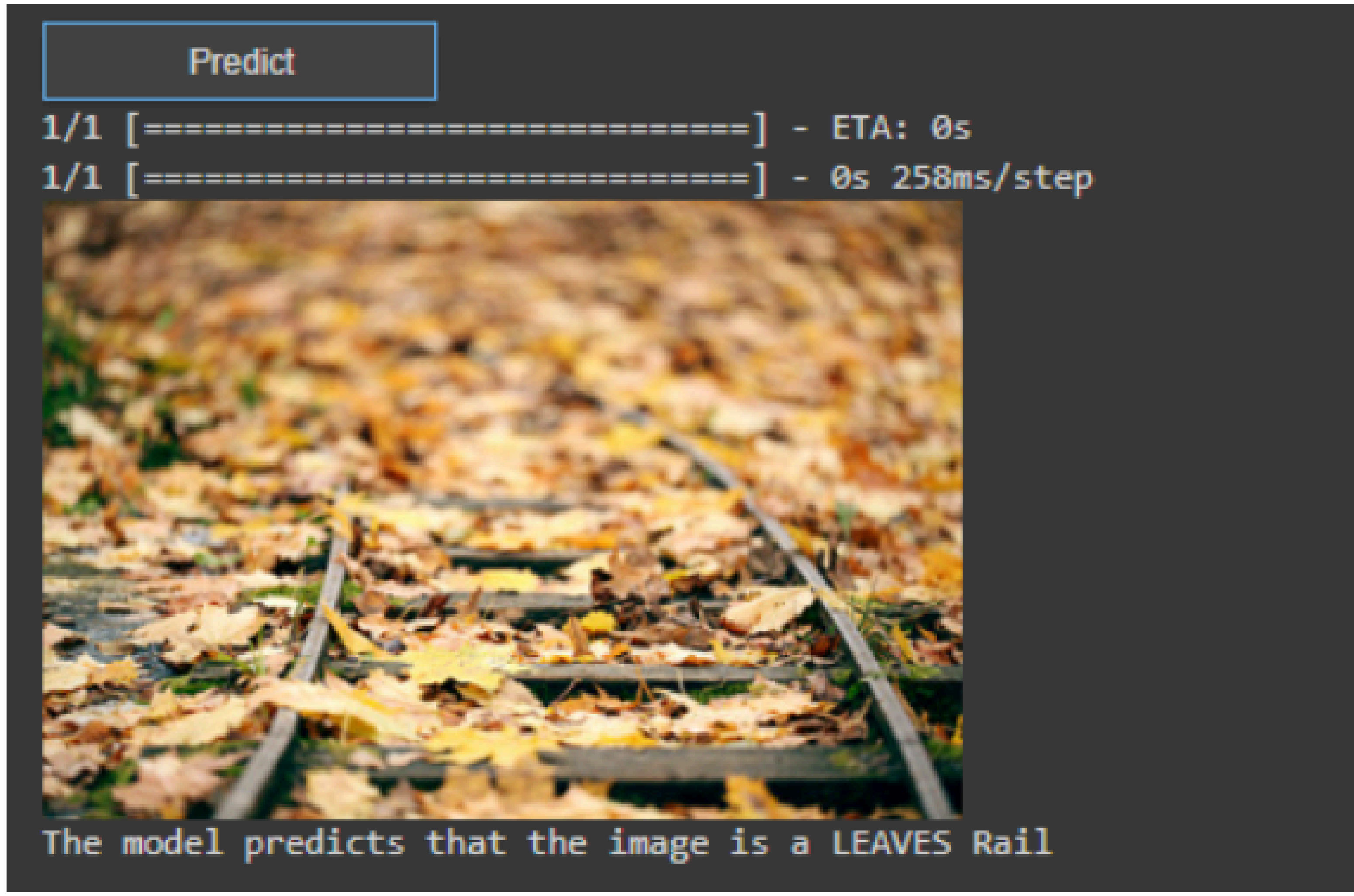

Fig 4.7 Training and Validation Accuracy and Loss

VGG19 achieved the highest accuracy of 99.67%, demonstrating superior performance in detecting leaf accumulation.

The Custom TensorFlow model also showed promising results with high accuracy.

# PREDICTION




Example images showing model predictions for leaf accumulation on rail tracks.
High accuracy in identifying both leaf-covered and clean tracks.
This Demonstrates the practical applicability of the developed system in real-world scenarios.

# DISCUSSION

AI-driven leaf detection systems can significantly enhance predictive maintenance by providing real-time detection and timely maintenance actions.
Integrating existing systems like leaf-busting trains and Water can optimize resource use and improve overall maintenance efficiency.
Potential to reduce downtime and maintenance costs and enhance the reliability and safety of rail services.

Limitations:

- Challenges in data collection due to regulations and limited availability of high-quality images.
- The computational intensity of model training requires access to high-performance GPUs for efficient processing.
- Dependence on high-quality, high-resolution images and potential performance impact under extreme weather conditions not fully tested.

# RECOMMENDATION

- Integrate models into existing railway safety systems to facilitate continuous monitoring and real-time predictive capabilities.
- Expand training datasets to encompass a broader range of environmental conditions and geographical variations, enhancing model robustness.
- Collaborate with technology developers to refine and customize models, ensuring scalable and economically viable solutions for diverse rail networks.

Future Work:

- Conduct further research on real-time application and scalability of the developed system, exploring integration with existing rail infrastructure.
- Investigate methods to improve computational efficiency, enabling broader deployment on less capable devices without compromising performance.
- Explore the practical implementation of this technology into existing rail maintenance and monitoring systems for a comprehensive solution.

# CONCLUSION

Developed a real-time system using machine learning and computer vision to accurately identify leaf accumulation, significantly enhancing rail safety and efficiency.

VGG19 model proved most effective with 99.67% accuracy, indicating the potential for practical deployment.

Research contributes to improving rail network efficiency and customer satisfaction, aligning with strategic visions for the future of rail services.

Future research should focus on expanding data robustness, improving computational efficiency, and integrating the system into existing maintenance frameworks.

# REFERENCES


Network Rail. (2021). Leaf-busting trains and their application. Retrieved from Network Rail website.

Network Rail. (2023). Water-Trak system for improving rail adhesion. Retrieved from Network Rail website.

Folorunso, M. O., Watson, M., Martin, A., Whittle, J. W., Sutherland, G., & Lewis, R. (2023). A Machine Learning Approach for Real-Time Wheel-Rail Interface Friction Estimation. Journal of Tribology, 145(9). https://doi.org/10.1115/1.4062373.

Louise, C., & Kirby, H. (2019). Challenges in Railway System Maintenance. Railway Research, 12(3), 123-134.

Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep Learning. MIT Press.

Chollet, F. (2017). Deep Learning with Python. Manning Publications.

He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (pp. 770-778).

James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). An Introduction to Statistical Learning: with Applications in R. Springer.

Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). ImageNet Classification with Deep Convolutional Neural Networks. In Advances in Neural Information Processing Systems (pp. 1097-1105).

University of East London

# THANK YOU


Ayo Mosaku
Engineering | 2024