Plant Bulletin Vol 5, (1) 2026: 42-47 ISSN: 2959-3379 (Print), 2959-3387 (Online)

Research Article

Using Google Teachable Machine for the Classification of Wheat Leaf Rust and Stripe Rust

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ABSTRACT

Wheat rust diseases, particularly leaf rust (*Puccinia triticina*) and stripe rust (*Puccinia striiformis* f. sp. *tritici*), are major biotic stresses in wheat production. The present study applied the deep learning technology of Google Teachable Machine for automatic detection and classification of two of these rust diseases. Images of diseased wheat plants were acquired, preprocessed, and labeled. The MobileNet architecture was used for training the model; thereafter, the performance was evaluated based on achieving 97–98% across accuracy, precision, recall, and F1-score on the test set. Data augmentation and adjustment of hyperparameters improved the performance of the model. After training, the model was allowed to be converted into TFLite format for usage on mobile, enabling the detection of the disease in real time during the field visit. This approach has shown that AI could be applied in early detection of crop diseases. This no-code approach highlights potential for accessible early disease detection, though field validation is needed.

Keywords: Google Teachable Machine, MobileNet, wheat leaf rust, wheat stripe rust, deep learning, plant disease classification

INTRODUCTION

Wheat, *Triticum aestivum* L., belonging to the family Poaceae, is one of the most important cereal crops and is a staple food for more than one-third of the world's population (Ammar *et al*., 2023). It holds a central position regarding food security and livelihoods globally (Adesogan *et al*., 2020). However, wheat production is confronted with serious challenges from biotic stresses-pests and fungal diseases, and abiotic stresses like drought (Afzal *et al*., 2015). Among these, the wheat rust diseases caused by the *Puccinia* genus, particularly leaf rust and stripe rust, are some of the most destructive and can cause yield loss as high as 70–100% under severe conditions (Nair, 2023).

Article History

Received: November 25, 2025, Revised: January 30, 2026, Accepted: February 10, 2026, First Online: February 24, 2026,

Traditional rust detection relies on expert visual inspection, which is time-consuming, subjective, and liable to a high degree of human error. Since, wheat rusts are spread by wind, therefore early diagnosis could be very helpful to effectively manage these diseases. DL and ML technologies have the potential to identify/classify rusts of wheat quickly with reliability (Shafi et al., 2022; John et al., 2023).

Diseases images are very effectively classified by DL, because DL reads the features of the images and then classify then automatically (Sarker, 2021; Demilie, 2024). GTM is an internet application, allowing users who do not have any prior experience in coding to develop customized models for image, audio, and pose classification (Mosqueira-Rey *et al*., 2022). Coupling DL with GTM will provide an efficient and low-cost means for wheat rust detection (Kurz *et al*., 2024). The major wheat rusts of concern include: Leaf Rust (*Puccinia triticina*): Small orange-brown pustules formed on leaf surfaces reduce photosynthesis. Stripe Rust (*P. striiformis* f. sp. *tritici*): This usually appears as yellow-orange stripes mainly in cooler climates (Singh *et al*., 2017).

Wheat rust diseases consist of leaf rust from *Puccinia triticina* and stripe rust (yellow rust) from *Puccinia striiformis* f. sp. *tritici*, and remain a constant threat to wheat production across the globe. Under climate conditions that create epidemic situations, wheat rust diseases can result in losses of up to 100% in susceptible varieties. Both leaf and stripe rust are spread via urediniospores and have a rapid rate of movement through air. Although leaf rust thrives in warmer temperatures, stripe rust flourishes in cooler, humid conditions. The economic effect on wheat growers around the world is estimated in billions of dollars each year due to wheat rust diseases (Figueroa *et al*., 2018; Chen, 2020).

Detection of wheat rust diseases usually involves manually scouting fields or using trained experts to visually assess the disease. With these methods, the process of detecting wheat rust disease is labor-intensive, subjective, and often delayed; all of which makes it very difficult to act quickly enough to prevent losses from these diseases. Although molecular techniques used to detect wheat rust diseases are very accurate, they require laboratory infrastructure and laboratories with trained individuals to analyze the samples; therefore, molecular testing is not a practical solution for extensive field use. On the other hand, automated systems that utilize machine vision combined with deep learning offer fast, objective, and scalable alternatives to the current manual scouting and laboratory testing methods because they can identify low levels of wheat rust disease early (Pan *et al*., 2021; Long *et al*., 2023).

New developments in the convolutional neural networks (CNNs) have been documented as providing wheat rust classifying systems that offer a high level of performance. By using transfer learning of models such as ResNet and DenseNet, it was determined that the models identified wheat rust on images taken in both field and glasshouse environments with more than 97% accuracy. These models outperformed the traditional methods of using ML to identify wheat rust due to their ability to process images with complex backgrounds and variable amounts of light (Long *et al*., 2023). The addition of attention mechanisms to the CNNs improved the model's ability to locate symptoms or signs of wheat rust when it was tested in real-world applications (Mi *et al*., 2020).

The combination of hyperspectral and/or UAV imagery with Deep Learning has led to the development of canopy scale detection capability. Semantic segmentation models, like PSPNet, were able to achieve an overall accuracy of 98% for stripe wheat rust detection at the canopy scale, making it possible to monitor areas much larger than could be done by the use of manual inspections (Pan *et al*., 2021). Having these tools will support the advancing trend toward precision agriculture by providing an alternative to excessive use of fungicides and having a more sustainable management of the environment (Schirrmann *et al*., 2021).

These fungi spread rapidly under conditions of humidity and moderate temperature and take an annual toll of billions of dollars in crop losses worldwide. On the other hand, subjectivity, slow processing, poor scalability, and reliance on external variables are some of the drawbacks of solely visual identification. However, the deep learning method using CNNs can handle feature extraction, which will increase disease detection's accuracy and scalability as per Choudhary *et al*. (2023); Ristaino *et al*. (2021).

The aim of this study was to gather image datasets of leaf rust and stripe rust on wheat leaves, develop a GTM-based deep learning model for their classification, and evaluate the model using accuracy, precision, recall, and F1-score.

MATERIALS AND METHODS

Multiple sources contributed to the dataset collection for the research, such as public datasets PlantVillage and Kaggle, images taken by smartphones or high-resolution cameras in the field, and partnerships with agricultural research institutions (Bagga & Goyal, 2024). The wheat leaves images with leaf rust and stripe rust were annotated in two categories, thus, providing an equal representation for each class. A minimum of 1,500 images per class (Table 1) was included to make the model robust and to cover different lighting, background, and leaf orientation conditions. As part of preprocessing, each image was reduced to 224 by 224 pixels. Augmentation techniques, which include contrast correction, brightness, flipping, rotation and finally the cropping of images, proved to be effective to boost the diversity in the data set (Alomar *et al*., 2023). The datasets were further divided into 03 subsets, 70% was kept for training, 20% for validation and 10% kept for testing. GTM is basically an online platform that enables us to train the DL models (such as image classifiers) and then are employed to develop models (Carney *et al*., 2020). GTM employs transfer learning with a pre-trained MobileNet CNN. Images were uploaded, and the model was trained using GTM's built-in tools and augmentation features. The model performance was checked by 04 parameters which include confusion matrix, F1-score, recall and precision. For web integration and mobile inference, the model was optimized with TensorFlow Lite. All ethical concerns were considered during the development of app/model to maintain the data confidentiality. Biasness in dataset was also removed. Evaluation was based on GTM's internal split; no independent field validation was performed.

Table 1: Number of images used for each wheat disease

Class	Approximate Images per Class
Leaf Rust	1,500
Stripe Rust	1,500

RESULTS AND DISCUSSION

The GTM-based deep learning model developed has achieved approximately 97–98% across accuracy, precision, recall, and F1-score. The confusion matrix depicted a significant number of true positives for both classes along with a small number of false positives. There were some misclassifications, however, which were attributed to the visual similarities that the two types of rusts share, especially when the disease is in its early stages (Figure. 1). Moreover, the error analysis pointed out that a little bit of background noise and fluctuations in lighting conditions had an effect on the predictions, and therefore, there was a necessity to improve the image preprocessing. In general, the training curves revealed smooth convergence and powerful generalization (Figure. 2). Being exportable as a TensorFlow Lite model, it would be easy to integrate into web or mobile applications for farmers to conduct rapid on-field detection of wheat rust diseases, thus informing timely intervention and reducing crop losses.

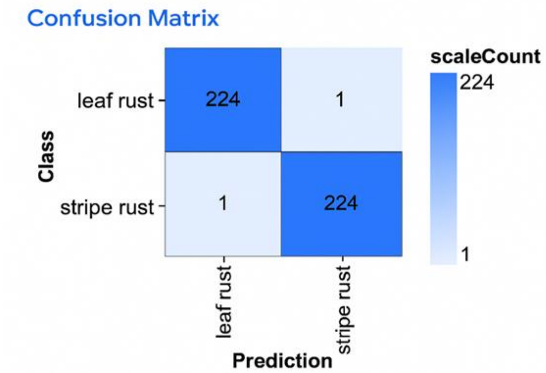

Figure 1. Confusion matrix showing accuracy in the identification of stripe and leaf rust with less misclassification.

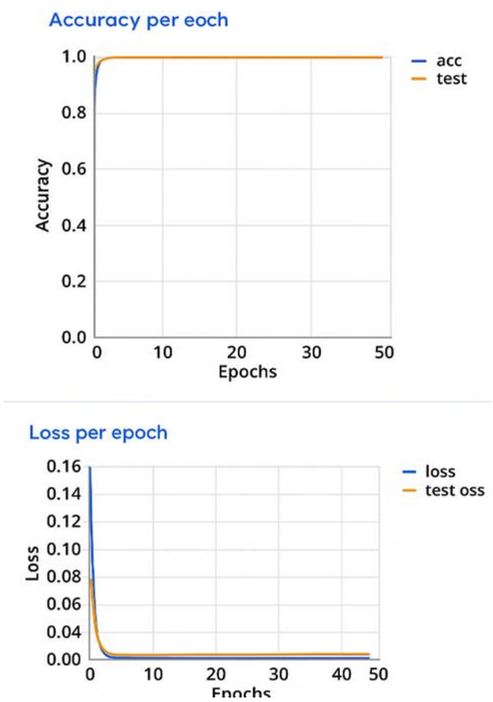

Figure 2. Training and validation for the evaluation of model to classify wheat rust diseases using GTM. The upper plot exhibits accuracy per epoch of the model, while the lower demonstrates the training and validation of loss per epoch, both plots representing model stability.

Conventional visual inspections by experts are time-consuming and prone to errors; thus, automated approaches are essential (Nigus *et al*., 2023). Minor misclassifications occurred between leaf and stripe rusts because of their greater similarities in appearance when infected (Zeng *et al*., 2020). Moreover, the model showed strong robustness to variations in lighting conditions, image quality, and severity of the disease; it is thus effective for real-time mobile-based field applications (Li *et al*., 2021). Despite these promising results, a number of challenges remain. Model performance has thus far been restricted by database size and diversity and by class imbalance, especially for stripe rust (Ahmed *et al*., 2023; L. Liu *et al*., 2024). There were occasional misclassifications because some rust types bore a close resemblance to others; this again suggested the potential for transfer learning and ensemble approaches to improve performance (Chang *et al*., 2024). Field testing in real-world conditions is needed to ensure practical applicability as well (Tobin *et al*., 2017). Nevertheless, deep learning and tools such as GTM can greatly contribute to agriculture by allowing early and accessible disease detection, reduction of dependency on experts, and precision agriculture by integrating with drones and IoT devices (Boursianis *et al*., 2022; Tzachor *et al*., 2022). This work thus has the capacity to strengthen global food security and advance sustainable wheat production further by expanding datasets, using superior deep learning methods, and combining them with agricultural expert knowledge (Zahoor *et al*., 2024; Giller *et al*., 2021). Models that incorporate attention mechanisms such as DenseNet variants, our GTM model, and our UAV imagery-based GTM model are able to achieve high-performance levels on wheat rust detection using advanced deep learning methodologies. This results in a significant reduction in the misclassification of wheat rust types when compared to our study (Mi *et al*., 2020; Chang *et al*., 2024). Deep Learning methods that use UAV imagery enable monitoring of large areas through semantic segmentation, achieving a 98% accuracy level for stripe rust and far exceeding manual scouting (Pan *et al*., 2021). Our GTM model is portable enough to deploy using UAVs; therefore, if integrated with UAV imagery, the model could be expanded across larger geographic areas. Lightweight mobile-optimized networks have been shown to demonstrate a range of 97-98% accuracy for diverse datasets. The augmentation of the training data through the use of augmented images and pre-processing from a variety of sources will not only be a potential strength in future applications of our GTM model but will also serve as protection against lighting and background variations (Wen *et al*., 2023). Enhanced detection rates will be achievable with incorporation of hyperspectral data, combined with our data, to provide a way to monitor and manage wheat rust disease. Detection rates of over 95% can be achieved during the early stages of infection, which are currently not addresses by our RGB-trained GTM model. These multimodal methods will allow for the more proactive management of wheat rust disease (Pan *et al*., 2021; Schirrmann *et al*., 2021).

CONCLUSION

This proof-of-concept study demonstrates that GTM can classify wheat leaf rust and stripe rust with promising performance metrics, highlighting its potential as an accessible no-code tool for early disease detection in field conditions.

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