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LETÍCIA ROSIM PORTO

Huanglongbing (HLB) Detection in Citrus Trees Using
Close-Range Multispectral Imaging and a Convolutional
Neural Network (CNN)



Presidente Prudente - SP
2025

Letícia Rosim Porto

Huanglongbing (HLB) Detection in Citrus Trees Using Close-Range Multispectral Imaging and a Convolutional Neural Network (CNN)

A Thesis submitted to the PPGCC (Programa de Pós-Graduação em Ciências Cartográficas) at the Faculty of Sciences and Technology, São Paulo State University – UNESP, in partial fulfilment of the requirements for the degree of Doctor of Science.
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IMPACTO POTENCIAL DESTA PESQUISA

Esta pesquisa visa contribuir para o avanço da agricultura sustentável, promovendo o uso do sensoriamento remoto proximal e da inteligência artificial para a detecção de doenças em campo como a Huanglongbing (HLB) em citros. Ao melhorar a detecção, reduz-se o uso de pesticidas, promovendo segurança alimentar e sustentabilidade.

POTENTIAL IMPACT OF THIS RESEARCH

This research aims to contribute to the advancement of sustainable agriculture by promoting the use of proximal remote sensing and artificial intelligence for the detection of field diseases such as Huanglongbing (HLB) in citrus crops. By improving disease detection, pesticide use can be reduced, enhancing food security and sustainability.

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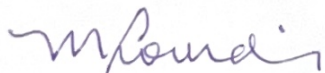
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RESUMO

Huanglongbing (HLB), ou *greening*, representa uma séria ameaça à produção citrícola global, especialmente no Brasil, maior produtor mundial de laranjas. Causado pela bactéria *Candidatus Liberibacter* e disseminado por psílídeos, o HLB leva a perdas drásticas de produtividade e à deterioração da qualidade dos frutos. Como não há cura conhecida, a detecção precoce e a erradicação de plantas sintomáticas, juntamente com o controle do vetor, são medidas cruciais. No entanto, o diagnóstico visual do HLB é desafiador devido à semelhança dos sintomas com deficiências nutricionais e à alta variabilidade influenciada por fatores ambientais. Os métodos tradicionais de detecção são subjetivos e demandam muita mão de obra, o que ressalta a necessidade de soluções escaláveis, não invasivas e precisas. Nesta pesquisa, foi criado um banco de dados de imagens multiespectrais com 14 bandas a partir da aquisição em dois talhões de um pomar comercial de laranjeiras no Brasil, abrangendo plano de fundos heterogêneos, variações de iluminação e diferentes condições das plantas. Este banco de dados contém 2.978 imagens proximais visível-NIR com altíssima resolução espacial e está disponível em acesso aberto para contribuir com a comunidade científica. Esta tese investiga o uso de aprendizado profundo (*deep learning*), com foco especial na adaptação de arquiteturas ResNet, para a detecção automatizada de HLB a partir de imagens multiespectrais proximais de folhas de laranjeira coletadas em condições naturais de campo. As arquiteturas ResNet (ResNet18, ResNet34, ResNet50, ResNet101) foram treinadas com diferentes configurações de conjuntos de dados (Talhão A, Talhão B e combinação Talhão A+B) e tipos de entrada (multiespectral e RGB). A ResNet34 treinada com o conjunto combinado (Talhão A+B) atingiu o maior F1-score (92,55%), enquanto a versão RGB alcançou 89,44%, confirmando o valor da informação espectral. Os modelos multiespectrais demonstraram melhor generalização e estabilidade, especialmente na detecção de plantas sintomáticas. Modelos treinados com conjuntos de dados mais diversos superaram consistentemente aqueles treinados com dados de apenas um talhão, ressaltando a importância da variabilidade dos dados de treinamento. A detecção da classe saudável foi, em geral, robusta entre arquiteturas e tipos de entrada, enquanto o desempenho para a classe HLB se beneficiou significativamente da riqueza espectral e da diversidade dos dados. Conclui-se que a adaptação de arquiteturas ResNet para dados multiespectrais é uma estratégia eficaz para a classificação de sintomas de HLB em condições reais de campo. Essa abordagem melhora a acurácia da detecção e apoia práticas de agricultura de precisão.

Palavras-chaves: Sensoriamento remoto proximal; Greening; Detecção de doença; Rede residual - ResNet; Agricultura de precisão.

ABSTRACT

Huanglongbing (HLB), also known as citrus greening disease, poses a serious threat to global citrus production, particularly in Brazil, the world's leading orange producer. Caused by the bacterium *Candidatus Liberibacter* and spread by psyllid vectors, HLB leads to drastic yield losses and deterioration in fruit quality. As there is no cure to this day, early detection and removal of symptomatic trees, along with vector control, are critical. However, visual diagnosis of HLB is challenging due to the similarity in symptoms to nutritional deficiencies and high variability influenced by environmental factors. Traditional detection methods are subjective and labour-intensive, highlighting the need for scalable, non-invasive, and accurate solutions. In recent years, remote sensing technologies combined with artificial intelligence have shown great potential for contributing to the automated detection of HLB-infected plants, supporting the development of more efficient and sustainable citrus production. In this research, a multispectral image database with 14 spectral bands was created from acquisitions in two plots of a commercial orange orchard in Brazil, encompassing heterogeneous backgrounds, varying lighting and diverse plant conditions. This database contains 2,978 visible-NIR proximal images with very high spatial resolution, and it is open-access to contribute to the scientific community. This thesis investigates the use of deep learning, particularly adapted ResNet architectures, for automated HLB detection using proximal multispectral images of orange tree leaves collected under natural field conditions. ResNet architectures (ResNet18, ResNet34, ResNet50, ResNet101) were trained using different dataset configurations (Plot A, Plot B and the combined Plot A+B) and input types (multispectral and RGB). ResNet34, trained on the combined dataset (Plot A+B), achieved the highest F1-score (92.55%), while the RGB version reached 89.44%, confirming the value of spectral information. The multispectral models showed better generalization and stability, particularly in detecting symptomatic plants. Models trained on more diverse datasets consistently outperformed those trained on single-plot data, emphasizing the importance of environmental variability. Healthy class detection was generally robust across architectures and inputs, whereas HLB class performance benefited significantly from spectral richness and dataset diversity. In conclusion, adapting ResNets for multispectral data is an effective strategy for classifying HLB symptoms under real-world conditions. This approach improves detection accuracy and supports precision agriculture practices.

Keywords: Proximal remote sensing; Greening; Disease detection; Residual Network - ResNet; Precision agriculture.

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1 CHAPTER 1: INTRODUCTION

1.1 RESEARCH CONTEXT AND MOTIVATION

Citrus was one of the most produced fruits worldwide in 2023, with 69.8 million tons (FAO, 2025). Among citrus varieties, oranges dominate global production, with Brazil leading as the largest orange producer and the biggest exporter of orange juice (Gonzatto; Santos, 2023). However, a significant number of orange trees have been affected by Huanglongbing (HLB) disease. This disease was first detected in the Americas in 2004, and it is estimated to infect 44% of orange trees in São Paulo State and the southwestern region of Minas Gerais, the primary citrus-producing area in Brazil (Gottwald; Graça; Bassanezi, 2007; Graham et al., 2024; Fundecitrus, 2024).

HLB, also known as citrus greening disease, is caused by the bacteria *Candidatus Liberibacter*, mainly transmitted by psyllid insects. This pathogen disrupts phloem activity, causes root decline, drastically reduces yields, and leads to significant loss of yield, decay of tree populations, or severe decreases in fruit quality and global marketability (Limayem; Martin; Shankar, 2024; Alquezar et al., 2022; Bové, 2006). As there is currently no cure for HLB-infected trees, management is primarily based on the eradication of infected trees and the control of insect vectors. Therefore, identifying infected plants on time and accurately is crucial for managing the disease.

Symptoms of the disease manifest in leaves, fruits, and roots. In leaves, the characteristic symptoms are asymmetrical yellowing, blotchy mottling and chlorosis. These blotchy mottles can be present in mature leaves throughout the tree canopy. Other symptoms include the presence of bright yellow shoots, corky mid-veins, yellowing of under-rib, and interveinal chlorosis in leaves (Gottwald; Graça; Bassanezi, 2007; Limayem; Martin; Shankar, 2024). However, symptom-based identification is often imprecise, as symptoms can be confused with other citrus diseases or nutrient deficiencies. Moreover, the visual symptoms can vary throughout the year and the environmental conditions, such as temperature (Barbedo et al., 2018; Limayem; Martin; Shankar, 2024). Symptoms are generally easier to see during autumn and winter (Gottwald; Graça; Bassanezi, 2007).

Early detection and eradication of HLB-infected trees are crucial for disease control, crop yield improvement, cost reduction, and reduction in the use of chemical insecticides. Nevertheless, HLB disease diagnosis by traditional methods is subjective, laborious and time-consuming. Non-invasive, automatic and more accurate techniques can facilitate large-scale HLB disease detection (Qiu et al., 2022).

Image-based proximal sensing for agricultural applications is a rising scientific field showing great potential, especially for perennial crops. In the case of HLB, the main information is found on the lateral faces of the canopy, making ground-view observations more relevant than aerial, top-down views. However, acquiring terrestrial

images under natural lighting presents several challenges, particularly due to non-uniform illumination and complex canopy geometries, which complicate acquisition in orchards (Rançon et al., 2023; Deng et al., 2019; Aquino et al., 2018; Wendel; Underwood; Walsh, 2018; Wendel; Underwood, 2017; Underwood et al., 2016; Deery et al., 2014). Radiometric calibration is often required to address lighting variations, especially in spectral imaging, where specific signatures are critical to detect symptoms. Yet, using calibration panels can be impractical over large areas. Conventional linear methods (e.g., chemometrics) are known to be sensitive to such variation (Wold, 1995), whereas more complex and nonlinear models, such as deep learning, may better handle inconsistent radiometry.

Previous studies have explored various sensor techniques and models to identify HLB-affected plants, including thermal imaging (Sankaran et al., 2013), chlorophyll fluorescence spectroscopy (Weng et al., 2021), visible spectroscopy (Gómez-Flores; Garza-Saldaña; Varela-Fuentes, 2019), near-infrared spectroscopy (Sankaran et al., 2011), and hyperspectral sensors (Porto; Imai; Tommaselli, 2022; Porto, 2021; Deng et al., 2019). While these approaches show promising experimental results, their practical application remains limited, largely due to high costs and viability.

Deep learning (DL) is a relatively new artificial intelligence technique that offers state-of-the-art modelling performance (Lecun; Bengio; Hinton, 2015). Convolutional Neural Networks (CNNs) are among the most prominent DL architectures for image-based classification and detection tasks in plant health (Sajitha et al., 2024; Wang et al., 2025). CNNs have been widely employed in agricultural applications, including plant disease recognition (Ma et al., 2018; Ai et al., 2020; Yadav et al., 2023), pest detection (Li et al., 2023; Yulita et al., 2023), and fruit detection (Espinosa et al., 2024; Kang et al., 2024). CNN models like AlexNet, GoogLeNet, LeNet, and ResNet have undergone improvements and have been effectively applied to the classification of plant diseases and pests (Wang et al., 2025).

Although manual pest and disease scouting remains common due to its accessibility, it is often limited by subjectivity, inconsistent accuracy, and low efficiency, particularly in large-scale operations. In contrast, DL models deliver greater accuracy, reliability, and scalability, offering solutions that address the limitations of traditional approaches and providing a robust foundation for advancements in precision agriculture (Wang et al., 2025). With sufficient, variate and adequate datasets, DL has shown strong potential for processing raw, heterogeneous field data (Kamilaris; Prenafeta-Boldú, 2018; Wang et al., 2025).

The present study extends the application prospects of deep learning for field-based plant disease diagnosis, providing a reference for artificial intelligence-based identification approaches and their application in real agricultural settings. Specifically, it explores the use of close-range multispectral imagery and CNN models for the detec-

tion of HLB under natural orchard conditions, aiming to support citrus producers in the early, reliable detection of infected plants, ultimately contributing to more sustainable and efficient disease management.

1.2 HYPOTHESIS

Considering that infection of citrus plants by the bacteria *Candidatus Liberibacter* induces physiological changes that alter their spectral behavior, and given the complexity of the environment in commercial orange orchards, the use of advanced non-linear models is appropriate to address the challenges posed by radiometric variability and to enable the classification of close-range multispectral images for identifying HLB-symptomatic orange tree leaves.

1.3 OBJECTIVES

The aim of this thesis is to develop an approach capable of identifying HLB-symptomatic orange trees under complex natural conditions, using close-range multispectral images acquired *in situ* and a deep neural network.

More specific objectives are: (i) to expand the knowledge of proximal sensing data acquisition in perennial crops and deep learning application to these data; (ii) to create a multispectral database of multispectral images of orange tree leaves with and without HLB symptoms collected *in situ*; (iii) to evaluate the effectiveness of deep residual networks (ResNets) in classifying HLB-symptomatic citrus trees using multispectral imagery, and to assess the impact of dataset diversity and spectral information on model performance; (iv) to evaluate and compare results of HLB-symptomatic citrus trees classification using RGB and multispectral images.

1.4 RELATED GRANTS AND INTERNATIONAL PARTNERSHIPS

This doctoral research is part of a thematic project, funded by FAPESP, and aligned with the United Nations Sustainable Development Goals, specifically focusing on digital agriculture (“High resolution remote sensing for digital agriculture”), and a Capes-PrInt project (“From Precision Agriculture to Prescription Agriculture: insertion of Unesp in the context of Digital Agriculture and Bioeconomy”). The CAPES-PrInt project funded a mobility period of one year at the French National Research Institute for Agriculture, Food and the Environment (INRAE). This collaborative work significantly contributed to the development of the proposed solution.

1.5 CONTENT OF THESIS

This thesis is composed of six chapters. Chapter 1 introduces the context of Brazilian citriculture and the threat of the HLB bacterial disease, highlighting the knowledge gaps that motivate our hypothesis, as well as the objectives of the thesis.

Chapter 2 presents related works and background, addressing overview and challenges of relevant topics to comprehend this thesis.

Chapter 3 introduce the construction of the dataset, describing in detail study area and data acquisition, as well as, database accessibility.

Chapter 4 is based on the work presented by Porto et al. (2024) in the ISPRS Technical Commission III Mid-term Symposium on Remote Sensing in Belém, Brazil. The work aimed to study the viability to adapt and apply the deep neural network ResNet to classify multispectral images of oranges trees between HLB-symptomatic and non-HLB.

Chapter 5 investigates the application of deep learning techniques, particularly ResNets for the detection of HLB disease in citrus orchards using multispectral and RGB imagery acquired under natural field conditions. This chapter discuss the relation between dataset, deeply of the model and spectral information.

As a final point, the Chapter 6 summarizes the key findings and limitations of our research and outlines future recommendations based on our results.

6 CHAPTER 6: FINAL CONCLUSION AND RECOMMENDATIONS

6.1 CONCLUSION

Amplifying knowledge and discussion about methods to efficiently detect HLB in citrus orchards is crucial for Brazilian agriculture. Due to the non-uniform distribution of HLB symptoms within the citrus canopy, aerial imagery may fail to capture symptomatic areas due to occlusion. In this context, close-range terrestrial image acquisition offers a valuable alternative for more accurate symptom detection.

Creation of the HLB Citrus dataset with 2,978 multispectral images available, contributes to the scientific community and to the development of machine learning approaches in plant disease detection and other close-range imaging uses. Initiatives like that contribute to the Global Development Goals for sustainable food production.

It is important to emphasize that the work was conducted using a highly complex dataset collected under real field conditions, which includes heterogeneous backgrounds, varying lighting, and diverse plant structures, as described in Chapter 3. Despite these challenges, including those caused by the absence of radiometric calibration, the models still achieved high performance in HLB detection with F1-score above than 90% with multispectral data and ResNets 34 and 101, indicating strong generalization capability and robustness, an essential requirement for practical agricultural applications.

Another important conclusion concerns the use of ResNet as an effective CNN architecture for HLB detection, as shown in Chapter 4. The modification of the first layer of the ResNet model enabled the use of multispectral images for this task. This adapted architecture can also be explored in other applications that require multispectral imagery.

Furthermore, it was observed that adding visible and non-visible bands to the RGB (490, 550, and 650 nm) images improves the results of HLB detection. ResNet34 trained with multispectral images of both plots showed a better ability to generalize to the training conditions. In HLB detection, the ResNet34 ability to identify true positive cases of infection (recall) improve from 85.92% to 91.83% with RGB and multispectral images, respectively.

The dataset, which includes images from two different years (2023 and 2024) and seasons (winter and spring), was important for increasing the robustness of the models. These conditions contributed to a more diverse set of samples for model training and better reflect real-world conditions in commercial orchards, which is essential for future reproducibility in other locations.

In conclusion, the most significant practical limitation to the effective dissem-

ination of deep learning technologies for plant disease classification is the difficulty in building sufficiently comprehensive databases. This data limitation imposes an intrinsic limit on the generalization capacity and maximum accuracy that can be achieved by deep CNN models, regardless of how advanced the architecture, especially when faced with the vast variability found in real field environments.

Ultimately, this research contributes to the development of precision agriculture tools capable of supporting reliable detection of HLB, promoting more sustainable management practices and reducing the environmental impact of citrus production.

6.2 RECOMMENDATIONS

Our findings demonstrated improvements related to the expansion of knowledge in the acquisition and use of proximal images in agriculture, specially in perennial crops as citriculture, and the use of ResNets models to detect HLB *in situ* acquired multispectral imaging. However, some recommendations are also highlighted for future works.

The first recommendation is to register the spectral bands before models training. The parallax effect is a significant challenge in close-range multispectral imagery, and pixel-wise registration of the spectral bands may improve classification results by ensuring geometric alignment of pixels. An alternative is to use a camera with a single lens and sensor for data acquisition, which inherently minimizes parallax effects due to its optical geometry.

Another suggestion is to continuously add more data to the dataset, including data from other orchards, citrus varieties and geographic regions to expand the number of trainable samples and variability of *in situ* situations. The characteristics of plant disease symptoms are influenced by color variation in plant tissues, plant genotype, and environmental conditions such as wind, temperature, sunlight, and other meteorological factors (Sajitha et al., 2024). Integration with other data sources, such as time-series information, may also contribute to more comprehensive plant health assessments. Even with the challenge of predicting the full extent of symptom variability associated with HLB disease, this addition can bring more robustness to the model, which should be reevaluated.

Although ResNet has proven to be an effective architecture for HLB detection using multispectral images, future studies are encouraged to explore and compare alternative convolutional neural network models. Evaluating different architectures could reveal performance gains or improvements in generalization. In addition, other combinations of spectral channels can improve the model's performance.

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