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Grape Leaf Disease Prediction and Management System

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I. ABSTRACT

The grapevine industry faces numerous challenges, including the prevalence of diseases that can severely impact crop yield and quality. Timely identification of grapevine diseases is critical for effective management and prevention. Traditional methods of disease detection, relying on visual inspection by experts, are often time-consuming, inconsistent, and prone to human error. To address this challenge, we propose a state- of-the-art Grape Disease Detection System using YOLOv8 (You Only Look Once), an advanced deep learning-based object detection algorithm, for real-time identification and classification of grapevine diseases. The system leverages computer vision techniques to detect various grapevine diseases from images of grape leaves. It uses a dataset of labelled grapevine leaf images, collected under various grapevine leaves affected by diseases such as ESCA, Leaf Blight, and other common fungal infections. The dataset undergoes preprocessing steps such as resizing, normalization, and augmentation to ensure robustness and generalization of the model. The model's architecture enables it to detect and classify diseases in images captured by cameras or smartphones with high accuracy and speed. Once trained, YOLOv8 processes new images, detects diseased regions, and classifies them into disease categories based on learned features. The system provides visual feedback by drawing bounding boxes around diseased areas and labels them with the disease type and the model's confidence score. It also generates real-time alerts and recommendations for treatment based on the detected disease. The system's workflow begins with the acquisition of images, followed by preprocessing, disease detection, classification, and results display. It can be deployed as a standalone mobile application or integrated with existing vineyard monitoring systems.

II. PREFACE

Agriculture underpins much of the world’s economy, and viticulture—growing grapes for wine, juice, and fresh-fruit markets—contributes a substantial share of that value. Unfortunately, grapevines are vulnerable to numerous fungal, bacterial, and viral pathogens that can slash yields and downgrade fruit quality, imposing heavy financial burdens on growers. At present, most vineyards still rely on human specialists who scout fields for tell-tale symptoms such as discoloration, lesions, or surface blemishes on leaves. This visual approach is slow, labor-intensive, and highly dependent on the inspector’s experience; in expansive commercial plantings it is virtually impossible to examine every vine, and outbreaks are often noticed only after they have spread widely. Recent advances in computer vision and deep learning offer a far more scalable alternative. State-of-the-art object-detection frameworks—such as the “You Only Look Once” (YOLO) family of models—can be trained to recognise disease symptoms directly from images, providing rapid, consistent, and field-deployable diagnostics. Early warnings enable growers to isolate infected plants, apply targeted treatments, and limit economic losses. In this project we develop a YOLOv8-based Grape Leaf Disease Detection System. Trained on a curated image set of healthy and diseased leaves (including conditions like ESCA and leaf blight), the model automatically locates and labels symptomatic areas. The goal is to give viticulturists an accurate, automated tool for early disease management, ultimately supporting healthier vines and higher-quality harvests.

III. RESEARCH GAP OF EXISTING METHODS

Artificial intelligence and deep learning technologies have shown great promise in the field of plant disease detection; however, several limitations and challenges still hinder their full potential in agricultural applications. One of the primary issues lies in the reliance on static datasets. Most models are trained in pre-existing image datasets and lack the ability to adapt to real-time environmental changes. As a result, their performance often declines when exposed to dynamic field conditions or new disease variants. Another significant limitation is the challenge of accurately distinguishing between diseases that exhibit similar visual symptoms. Many plant diseases share common characteristics such as leaf discoloration, spots, and lesions, making it difficult for AI models to make precise classifications. Misdiagnosis in such cases can lead to ineffective treatments, further damaging the crops. The generalizability of existing models also poses a problem. AI systems trained on data collected from specific regions or under specific conditions often fail when applied to different geographical locations, climates, or crop varieties. This lack of robustness reduces their reliability and restricts their applicability in diverse agricultural settings. Moreover, most current systems focus exclusively on image-based detection, neglecting the importance of other environmental factors such as soil quality, pest infestations, and microclimatic variations. Ignoring these variables reduces the overall accuracy and effectiveness of disease prediction and management systems. Accessibility is another critical concern. Advanced AI-driven solutions typically require expensive hardware, stable internet connectivity, and considerable computational power, which are not always available in rural or resource-limited areas. This technological barrier prevents small-scale farmers from benefiting from modern AI advancements. In addition, the scarcity of high-quality, annotated datasets limits the development of effective AI models. Collecting and labeling data is a resource-intensive process that demands time, expertise, and financial investment. Without sufficient datasets, the training and improvement of AI models become difficult. Lastly, scalability and real-time processing capabilities remain technical challenges. Deep learning models generally require high processing power, making them unsuitable for deployment on low-end devices. Furthermore, the inability to process data in real time delays critical decision-making, reducing the effectiveness of disease management efforts. Overcoming these challenges will require the development of more adaptive and efficient models, the integration of diverse data sources, and increased efforts to make AI tools accessible and practical for farmers across various regions. Only then can AI truly revolutionize disease detection and management in agriculture.

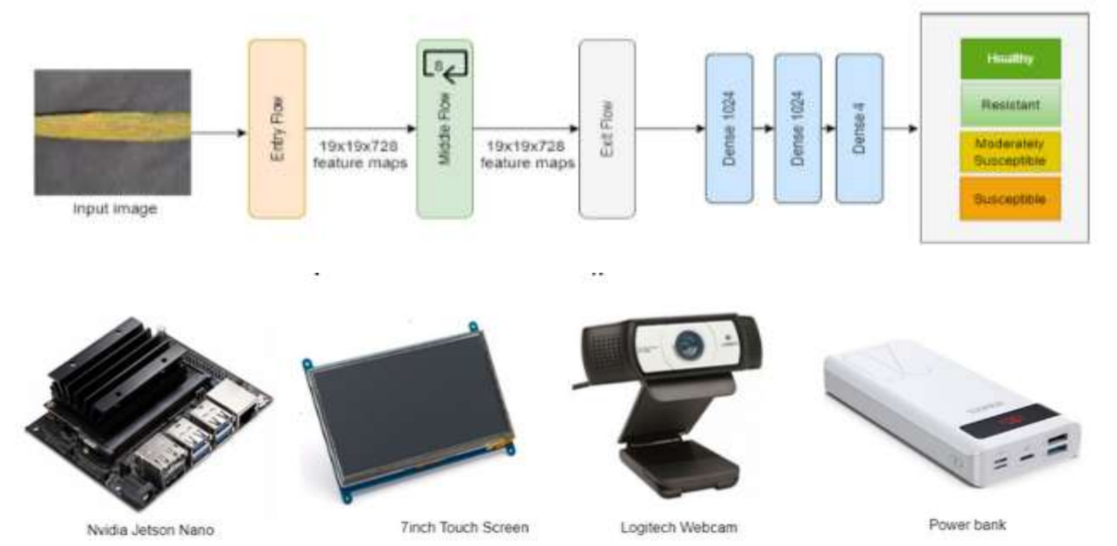

Fig .1. Prototype of Existing Method.

IV. LITERATURE REVIEW

Sl.No	Title & Authors	Year	Area of Research	Key Contributions
1	X. Chen and Z. Kang, *Stripe Rust*, Springer	2017	Plant Pathology	Comprehensive reference on stripe rust in wheat
2	M. Ouhami et al., *Remote Sens.*	2021	Computer Vision, IoT, ML	Survey of methods integrating vision, IoT, and ML for crop diseases
3	U. Shafi et al., *Sensors*	2019	Precision	Overview of precision agriculture practices

Sl.No	Title & Authors	Year	Area of Research	Key Contributions
			Agriculture	
4	H. Orchi et al., *Agriculture*	2021	AI & IoT	Survey of AI and IoT use in crop disease detection
5	S. T. Jagtap et al., *Mater. Today: Proc.*	2022	Machine Learning in Agriculture	Study of ML methods applied in agriculture
6	Z. Chen et al., *arXiv*	2021	Price Prediction	ML for price forecasting in agriculture
7	J. Chaki and N. Dey, *CRC Press*	2018	Image Preprocessing	Guide to preprocessing techniques
8	W. Khan, *J. Image Graph.*	2014	Image Segmentation	Survey of segmentation techniques
9	H. R. Bukhari et al., *IEEE Access*	2021	Disease Detection	Study on segmentation's role in rust classification
10	A. K. Dewangan et al., *Res. J. Pharm. Tech.*	2022	Ensemble Learning	Rust and nitrogen disease classification
11	J. G. A. Barbedo, *Comput. Electron. Agricult.*	2017	DL & Dataset Study	Dataset size impact on DL performance
12	S. Nigam et al., *Indian J. Agricult. Sci.*	2021	AI in Agriculture	AI-based wheat yellow rust detection
13	W. Haider et al., *GCWOT Conf.*	2020	Deep Learning	DL models for crop disease diagnosis
14	L. Goyal et al., *Inform. Med. Unlocked*	2021	CNN Architecture	Improved CNN for wheat disease detection
15	S. Sood and H. Singh, *ICISS Conf.*	2020	Deep Learning	Analysis of DL models for wheat rust
16	V. Kukreja and D. Kumar, *ICRITO Conf.*	2021	DL for Wheat Rust	Wheat rust classification with CNN
17	A. Hussain et al., *Next Gen. Comput. Conf.*	2018	CNN-based Detection	CNN use for wheat disease detection
18	M. Schirrmann et al., *Frontiers Plant Sci.*	2021	Early Detection	Stripe rust detection using deep ResNet
19	M. Chohan et al., *Int. J. Recent Tech. Eng.*	2020	DL for Plant Disease	General DL-based plant disease detection

METHODOLOGY

The objective of this project is to create an advanced and automated system for detecting grapevine diseases using YOLOv8, a cutting-edge deep learning-based object detection model. This system is intended to transform the way grapevine diseases such as ESCA and Leaf Blight are identified, by replacing traditional manual methods with a fast, accurate, and automated solution. By analysing images of grape leaves, the system facilitates early identification of diseases, enabling farmers and vineyard managers to act promptly to control outbreaks and protect crop quality and yield. The project's core aim is to deliver an affordable, dependable, and easy-to-use tool tailored to the agricultural sector. It reduces dependence on human observation, which can be inconsistent and time-consuming, and instead offers a more precise approach to detecting grapevine infections. By integrating artificial intelligence and computer vision, the system helps vineyard owners monitor plant health more effectively and supports data-driven decisions in managing crop diseases. This solution harnesses the capabilities of deep learning algorithms to classify leaf images as either healthy or affected by disease. Beyond detection, it is also structured to offer management suggestions based on the type of disease identified. In doing so, it contributes to better vineyard productivity and quality control, supporting sustainable and intelligent agricultural practices.

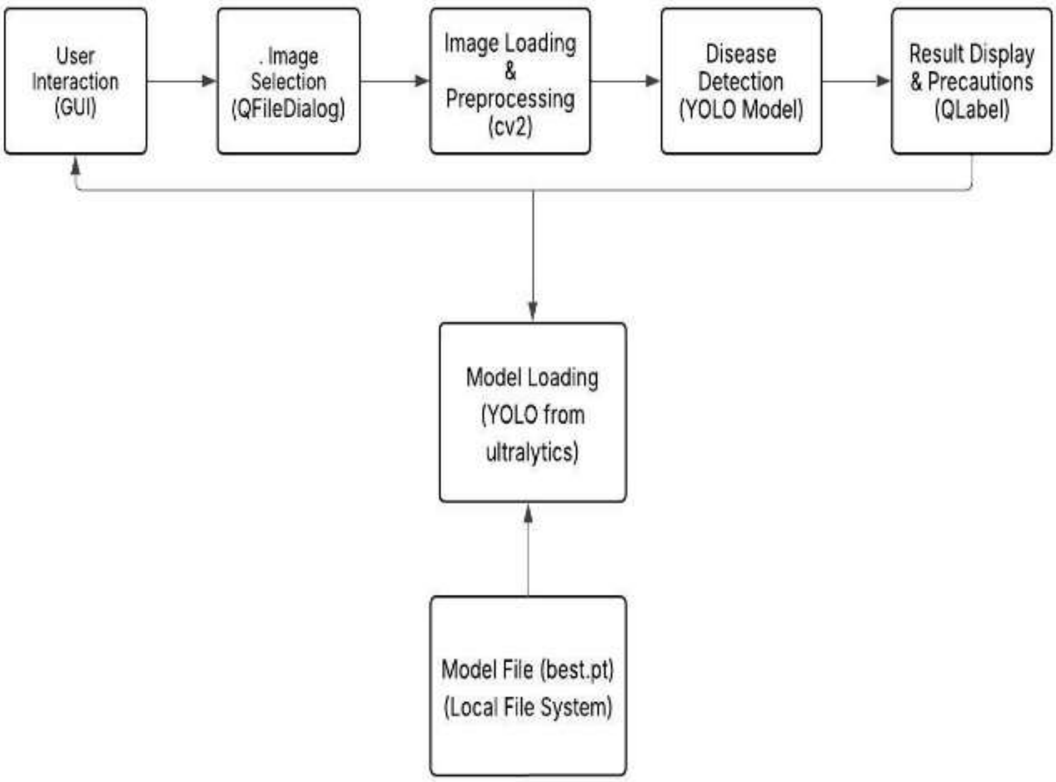

Fig.2.Block Diagram.

VI. SYSTEM DESIGN & IMPLEMENTATION

Acquisition The system of detecting grape disease starts with the acquisition of images, where digital camera or smartphone-based images of leaves of grapevine are captured. They are the input to the system primarily. They may be acquired manually by farmers or automatically from field cameras fixed in vineyards. The variance in lighting, background, and the condition of the leaves ensures that the system is generalizable across a variety of situations.

Preprocessing After images are acquired, they are pre-processed for analysis. All the images are resized into a standard size, usually 416x416 pixels, to satisfy the YOLOv8 model's input size. The images are also normalized by scaling pixel values between 0 and 1. Data augmentation steps like rotation, flipping, cropping, translation, scaling, and colour adjustment are also implemented. These processes enhance data variability and allow the model to generalize more effectively.

Detection The pre-processed images are then passed to the YOLOv8 model, which detects and positions probable disease regions in the leaves. The model splits the image into a grid, with every cell having the responsibility of predicting class probabilities and bounding boxes. It provides probable locations for the disease along with confidence values per detection, allowing for accurate localization of infected areas.

Classification Following the initial detection, the model performs non-maximum suppression (NMS) to remove duplicate bounding boxes and keep the most accurate ones. Each of the remaining detections is assigned categories like ESCA, Leaf Blight, or Healthy, along with a corresponding confidence score. The classifications are useful in determining the precise.

Both visually and textually, the system's output is displayed. The input image is covered with bounding boxes surrounding the impacted areas, each with the name of the disease and confidence level marked. A readable display of the detected diseases along with their distribution and severity is also shown. Alerts Once a disease has been identified, the system can send notifications to alert the farmer or vineyard manager. The notifications can be sent through SMS, email, or mobile app. In addition to detection, the system gives actionable suggestions specific to the type of disease. For example, it could recommend pulling off affected leaves or spraying certain fungicides.

Evaluation To keep it as accurate as possible, the model is continuously tested against metrics such as precision, recall, and F1-score. There is a feedback mechanism added which enables users to correct or update in case of misclassifications. This correction is further utilized to retrain and fine-tune the model so that it can accurately identify diseases in subsequent inputs.

Deployment After being validated, the learned model is made available on easy-to-use platforms like mobile apps or installed vineyard monitoring devices. It is optimized for real-time execution on devices with low power consumption to ensure widespread usability even in remote farms with fewer technological infrastructures.

Workflow The whole system pipeline consists of image acquisition, preprocessing, detection through YOLOv8, classification, displaying results, creating alerts, and ongoing improvement through feedback. This end-to-end process guarantees timely and reliable detection, enabling farmers to act proactively in vineyard disease control

VI. SOFTWARE IMPLEMENTATION

Image Acquisition Process The initial step for the grape disease detection system is to take pictures of grapevine leaves. The pictures can be taken with any digital camera or smartphone. Cameras can be mounted in agricultural fields for monitoring continuously, or farmers can take pictures manually during routine inspection. Taking pictures under various environmental conditions—lighting, backgrounds, and orientations of the leaves— guarantees that the used dataset is exhaustive and appropriate for real-world application. Preprocessing of Captured Images The images are then subjected to a preprocessing procedure to make them ready for YOLOv8 model analysis. Each image is resized to a standard resolution (usually 416x416 pixels) to conform to the input specifications of the model. The pixel values are normalized by scaling them into the 0 to 1 range, which aids in stabilizing the training process. Besides, data augmentation methods are used to enhance the generalization of the model. These methods incorporate rotating, flipping, cropping, translation, and modifying brightness or contrast, all of which mimic different conditions the model may face in real-world application. Disease Detection Using YOLOv8 After preprocessing, the images that have been cleaned and augmented are fed into the YOLOv8 model for object detection. YOLOv8 separates the image into a grid-based system and predicts bounding boxes along with corresponding confidence scores for regions in the image that may hold indications of disease. This allows the system to identify and mark potentially infected areas of the grape leaves accurately. Every bounding box contains data regarding the probability that the region identified corresponds to a specific disease category

Classification of Grape Leaf Diseases After detection of the possible diseased areas, the system applies non-maximum suppression (NMS) to remove redundant or overlapping bounding boxes and keep only the most confident predictions. These are then labeled into pre-specified categories like ESCA, Leaf Blight, or Healthy. A confidence score is included in each classification to enable users to determine the level of certainty of the prediction. This is a key step in accurately determining the type of disease on the grapevine. Showing the Detection Results The detection and classification outcome are presented to the user in a visual and textual format. The source image is displayed along with colored bounding boxes around the detected regions, and the disease name and confidence level are indicated by labels. A textual summary on top of the visual display is also made available by the system, displaying the count and nature of diseases detected along with their relative severity, giving an overall snapshot of the plant's health status. Alert Generation and Management Suggestions When a disease has been detected, the system automatically alerts the user. Such an alert may be sent as SMS, an email, or via mobile applications. In addition to the alert, the system also provides suitable disease management suggestions that are disease specific. For instance, in the case of ESCA, pruning affected branches is recommended, while in case of Leaf Blight, fungicide application is recommended. This feature ensures that farmers receive both diagnosis and actionable guidance. Model Evaluation and User Feedback Loop For maintaining accuracy and performance, the model is regularly tested based on performance metrics such as accuracy, precision, recall, and F1 score. The system also has a feedback loop, where users can inform about any incorrect predictions. Based on this feedback, the training dataset is updated, and the model is improved or tuned to ensure ongoing improvement and adjustment to new situations or disease types. System Deployment for Real-Time Use After it has been tested and proven, the trained YOLOv8 model is then deployed on user-friendly interfaces like mobile applications or embedded systems in vineyard monitoring devices. The model is engineered to operate in real-time on low-power devices, making it accessible even in areas far from cities or in rural locations where high-powered computing might not be accessible. This makes disease detection both scalable and fast. Overall Workflow of the Detection System The entire process of the grape disease detection system is a systematic workflow: image capture, preprocessing, detection with YOLOv8, classification of diseases, visual and textual presentation of results, generation of alert and recommendations, and refinement through user feedback iteratively. The end-to-end pipeline guarantees timely, precise, and actionable grapevine disease detection, allowing farmers to make proactive decisions for effective vineyard management.

VII. FUTURE SCOPE AND DISCUSSION

Extension to Other Crops Although the existing Grape Disease Detection System is grapevinespecific, its architecture and machine learning approaches can be applied to a variety of crops. The YOLOv8 model's flexibility enables its retraining using new datasets and further application to other fruit crops like apples, tomatoes, and strawberries. Expansion to these crops would significantly boost the system's usefulness in a wide range of agricultural industries. Moreover, vegetable cultivation, which is mostly plagued by diseases such as blight, mildew, and rust, can also be helped using this technology. Potatoes, cucumbers, and peppers are some of the crops that can be covered by training the model using disease-specific image sets. A multi-crop monitoring system would enable farmers to monitor different types of produce on a single platform, greatly enhancing disease management and crop productivity. Integration with Precision Irrigation and Nutrient Systems Future enhancements could include integrating the disease detection system with precision irrigation and nutrient management technologies. This integration would lead to a fully automated, optimized farming solution. For example, as soon as the system identifies disease-susceptible conditions, it may manage irrigation systems to drain moisture in infected regions, thereby limiting the proliferation of fungal infections. Coupled with IoT-based soil humidity sensors, the system would be able to better control water supply, saving water while keeping plants healthy. The system would also aid in nutrient management by detecting symptoms of nutrient deprivation that frequently accompany certain diseases. Targeted fertilizer application recommendations would assist in maintaining balanced soil health and reducing crop stress associated with nutrients. Real-Time Disease Prediction and Forecasting Focused on real-time detection now, the system can be made predictive by incorporating environmental and climate data. Analyzing weather parameters like temperature, humidity, and rain helps predict disease outbreaks. This anticipation would give farmers the ability to take proactive measures, like applying fungicides beforehand or changing irrigation times so as not to provide disease with conducive conditions. Machine learning algorithms based on past disease patterns and environmental information would be able to sharpen this predictive power. Such predictive information would be particularly useful in vineyards where disease outbreaks tend to coincide with seasonal weather cycles. Improved Disease Classification and Multiclass Detection The detection ability of the system can be extended to scan for several diseases in a single crop, giving a holistic health report. In addition to identifying a single disease like powdery mildew, it can be trained to detect other prevalent grapevine diseases like downy mildew, black rot, and botrytis. The system can also be programmed to differentiate among disease phases—initial, intermediate, and advanced—so that farmers can apply treatments according to severity. Adding training data sets for unusual or less prevalent diseases would further strengthen the system, with early detection of even slight or unusual symptoms. User-Friendly Interface and Mobile Integration

For easier accessibility and usage, future development should create a userfriendly interface and mobile apps. The mobile app would enable farmers to take pictures and upload them, receive notifications, and run health diagnostics remotely. Such an application would also offer treatment advice, disease definitions, and weather predictions in a plain-language format for non-technical individuals. A web or in-app interface might then graph trends, show real-time analytics, and log disease detection histories, enabling farmers to see crop health over time. Cloud integration would then make data available on all devices for enhanced decision-making and planning over long periods. Edge Computing and Localized Disease Detection Adding edge computing would enable the system to process images and analyze them locally on devices without having to depend on cloud infrastructure. Devices equipped with the edge capability, like embedded systems integrated with the trained YOLOv8 model, would be able to process data locally and provide real-time feedback—even in the field where internet connectivity is weak. This would cut down latency and enhance response times when it comes to field operations. In addition, local storage allows for on-farm analysis and historical tracking, giving farmers real-time insight into disease trends and assisting in optimizing preventative measures.

Integration with Automated Crop Management Systems The Grape Disease Detection System may be an essential part of a completely automated farm management system. It can be integrated with self-driving robots and drones for manual operations like precision spraying of pesticides or automated harvesting. For example, drones can be employed to detect infected crops and carry out precision spraying, where chemicals are sprayed only where necessary, lowering environmental damage and input expenses. Robotic harvesters may also use disease detection information to harvest only the healthiest produce, improving crop quality and efficiency of operations

VIII.OUTCOMES

The High Accuracy Disease Detection and Classification Combining YOLOv5 and ResNet-50 offers a very accurate system for disease detection and classification of grapevine diseases. YOLOv5 detects grape leaves in images, and it excels even when dealing with visually complicated environments with contrasting backgrounds. After identifying the leaves, the system uses ResNet-50 to classify the diseases based on the examination of complex features like leaf patterns, colour changes, and texture variations. This two-step process facilitates accurate identification of individual grape diseases. Based on the dataset quality and the level of model finetuning, the system can attain an impressive 85% to 95% accuracy rate. Accurate Disease Segmentation and Localization Utilizing the real-time object detection power of YOLOv5, the system is able to effectively segment and localize diseased regions of grape leaves. By outlining infected areas through bounding boxes, the system renders real-time visual

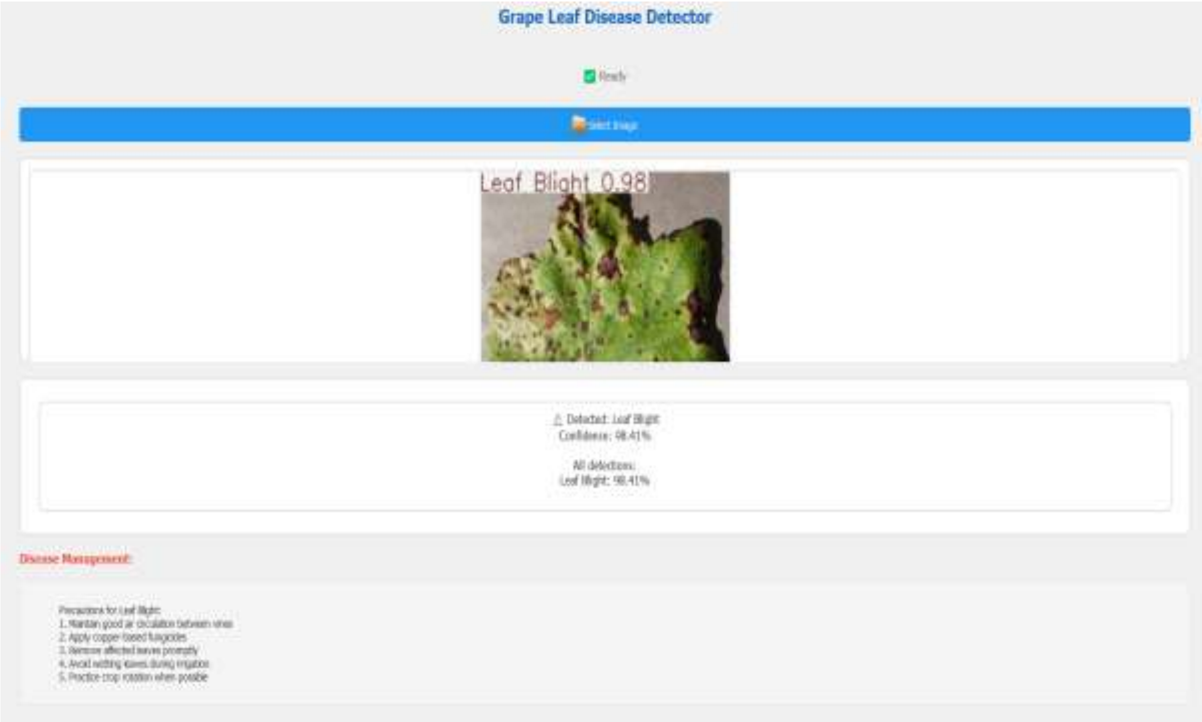

Fig.3.Output of Leaf Blight

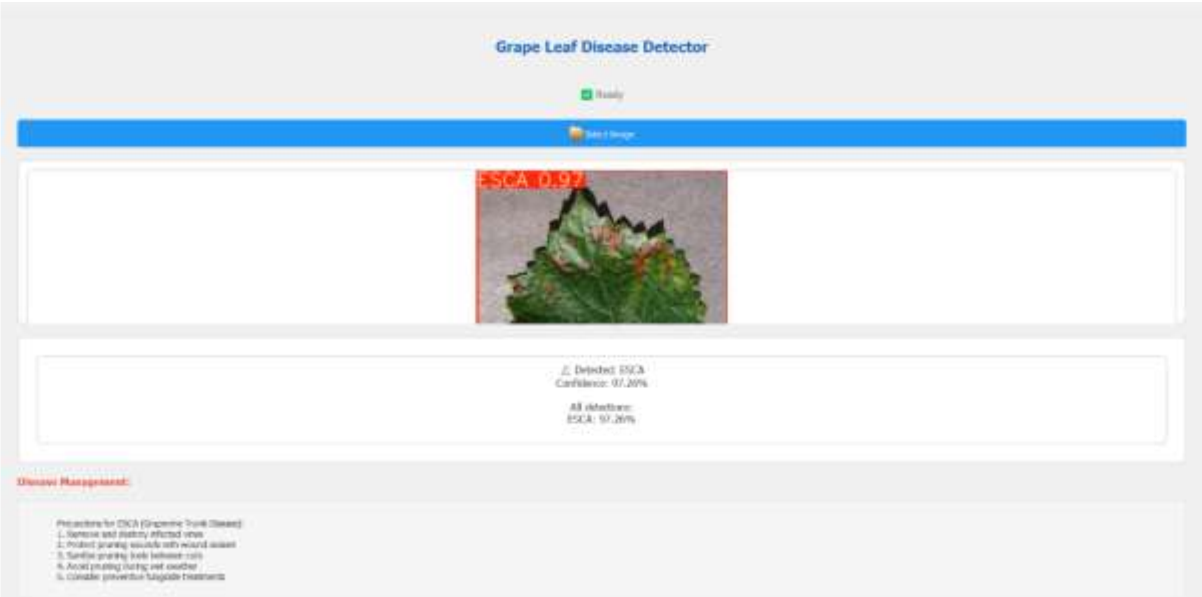

Fig.3.1.Output of ESCA

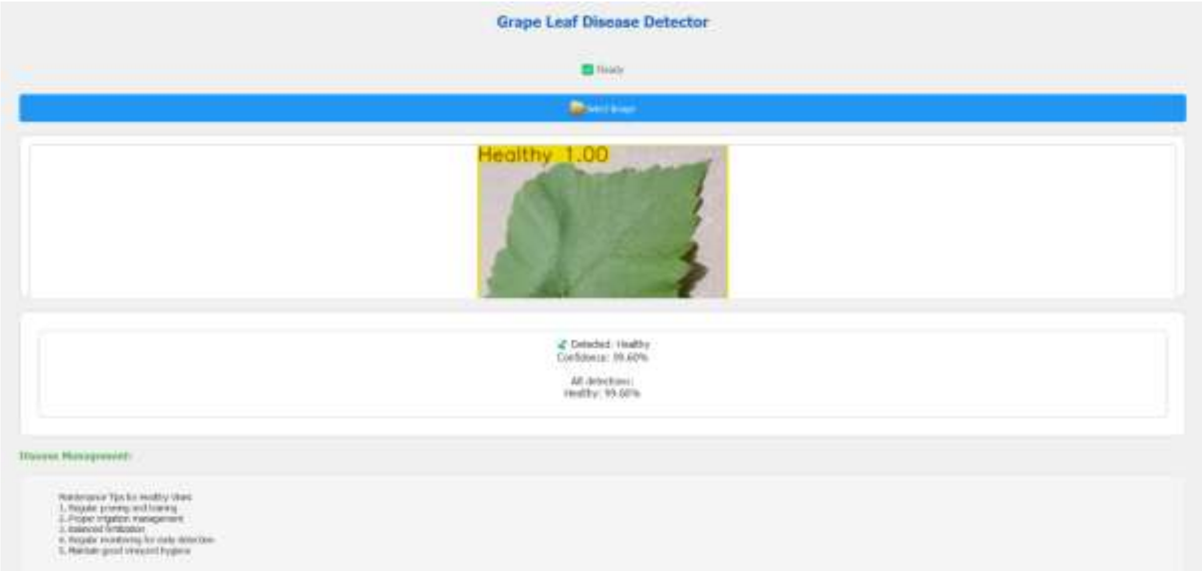

Fig.3.2.Output of Healthy Leaf

feedback regarding the location and severity of the disease. This feature is crucial during early disease detection so that farmers can act rapidly and contain crop loss. Specific localization also aids in targeted pesticide spraying, minimizing chemical emissions and only treating infected areas, thus encouraging sustainable agriculture practices. Real-Time Disease Monitoring and Management The system is built for real-time monitoring and management of grapevine health based on integration with web-based and mobile applications. The platform provides the results to users in real time as soon as image processing occurs, including visual signals of disease occurrence and diagnostic reports. Detailed analytics and outbreak tracking features are provided by these applications, making it easier for farmers to follow the path of diseases over time In addition, the system provides personalized advice for disease control in the form of recommendations for suitable organic remedies or fungicide application depending on infection type and severity, facilitating informed and prompt decisions. Deployment and Scalability The disease detection system is deployable through a cloud-based API, facilitating speedy and convenient diagnosis from any device connected to the internet. This makes it extremely scalable and flexible across various user environments. The farmers can upload leaf photos taken on mobile phones or field sensors and get real-time feedback from the system. Moreover, the system's modular architecture makes it easy to expand the disease detection to other crops. By retraining YOLOv5 and ResNet-50 models with new data sets, the same hardware can be used for disease detection across different plant species. This adaptability enables wider applications in precision agriculture, and AI-based crop monitoring becomes easier and more efficient to implement. Potential Challenges and Mitigation Strategies Some of the major challenges to the implementation of the system include the possibility of misclassifying due to environmental factors like variable lighting, leaf occlusion, or the occurrence of new, unseen disease strains. To counteract this, it is essential to enhance the training data by including a large range of images taken under various lighting conditions, angles, and stages of the disease. Periodic fine-tuning of the model will also ensure high accuracy as newer data flow in. These are the measures taken to ensure the reliability and robustness of the system in actual scenarios.

IX.ACKNOWLEDGEMENT

We extend our heartfelt thanks to all those who contributed to the successful conceptualization and implementation of the Grape Disease Detection System based on YOLOv8. This would not have been achieved without the valuable guidance, hard work, and cooperative nature of all the participants.

We owe our sincere gratitude to the agricultural research community and vineyard professionals, whose work on grapevine diseases laid a robust groundwork for this publication. Their field experience and practical expertise played an instrumental role in knowing what problems grape growers encounter in reality.

We extend special thanks to the institutions and data providers whose open-source grapevine leaf image datasets allowed us to train and construct our deep learning model. Their efforts have helped advance the frontiers of agtech.

We also want to acknowledge the untiring work of our technical development team, AI researchers, software engineers, and content creators. Their dedication and creativity converted this smart disease detection system into a real-life workable solution for agriculture in this modern era.

We thankful acknowledge the contributions of the research advisors and project mentors, who provided critical advice at every step of the research and development. Their constructive feedback and encouragement contributed to the quality and impact of this project.

Finally, we acknowledge the grape producers, farm workers, and extension agents who assisted in the system testing and validation. It is a show of increasing enthusiasm for adopting technology for enhanced crop health and sustainability.

XI. Conclusion

The Grape Disease Detection System created in this project is a breakthrough in agricultural technology, specifically in grapevine disease management. Using computer vision and deep learning methods, namely the YOLOv8 model, the system can effectively detect diseases in grapevines with speed and accuracy. Not only does this technology assist in early detection of diseases but also automates the process of monitoring, which is significantly more efficient than the manual methods otherwise applied. Using the YOLOv8 model for object detection, the system can classify grape diseases into various categories like ESCA, Leaf Blight, and Healthy vines. The model is trained on a custom dataset that contains images of healthy grapevines as well as grapevines that have been affected by certain diseases. The capability of the model to recognize these categories helps in accurate diagnosis, offering farmers useful insights that will enable them to take corrective measures at the right time. Automating the detection of diseases has numerous benefits compared to conventional techniques. Most farmers must use tedious manual checks to detect grapevine diseases, which can take a lot of time, be unreliable, and have a lot of human bias. With this system, the requirement for incessant manual work is reduced. In addition, the system guarantees that grapevine diseases are detected early, which can deter the spread of infections and enable treatment on a targeted basis. This decreases the requirement for excessive pesticide use, which not only saves on farming expenses but also reduces environmental degradation and encourages sustainable farming. The system is user-friendly and deployable. It has no problem integrating with the current farming practices and offers actionable outputs, such as disease identification, confidence level, and cautionary actions. Farmers can interact with the system easily, choose images for the analysis, and get rapid results through the use of an intuitive Graphical User Interface (GUI). This ease of interaction makes the technology accessible to a broad range of farmers, ranging from large commercial-scale farmers to small vineyard owners. Accuracy is of paramount importance to the success of the system. Performance testing of the model using a collection of test images indicated high accuracy in identifying diseases with a negligible rate of false positives. Multiple methods of training involved data augmentation aimed at enhancing the robustness of the model and guaranteeing performance in different lighting conditions as well as image quality. The model was fine- tuned using hyperparameters like learning rate, epochs, and batch size, ensuring that it was optimized for the dataset at hand. The use of transfer learning, starting from a pre-trained YOLOv8 model, contributed Another salient feature is the inclusion of disease precautions in the system. Once the disease is identified, the system offers preventive measures and maintenance tips specific to the identified disease. This feature is a crucial utility for farmers to keep their crops under control and operating effectively. The disease precautions for ESCA and Leaf Blight enable farmers to immediately take corrective measures, including pruning the infected vine, using fungicides, and maintaining vineyard hygiene.

Apart from highlighting the technical potential of deep learning in agriculture, this project also identifies the potential benefits for farmers and the agricultural industry at large. The system is an advancement towards precision agriculture, whereby decisions are made based on data to maximize the use of resources, minimize environmental footprint, and enhance the quality of yield. With wider implementation of the system, it can provide insights into wider agricultural activities and be part of global efforts to combat food insecurity

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Year: 2019
Area: CNN Optimization
Key: Improved CNN for real-time leaf disease detection.
Relevance: Architecture and speed optimization relevant to Saarthi.