THE OBJECTIVE OF THIS STUDY WAS TO DETERMINE HOW ENVIRONMENTAL VARIABILITY INFLUENCES THE DETECTION OF DISEASES OF GRAPE

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ABSTRACT
A variety of fungal, bacterial and viral diseases are very common in grape production. In recent times, image-based Artificial Intelligence (AI) and Machine Learning (ML) have emerged as potent tools for speedy and automat- ed disease detection. Unfortunately, such models are highly sensitive to envi- ronmental variation, and the accuracy and reliability of models is heavily de- pendent on environmental differences. Detection performance is influenced by visual symptom, disease progression, image quality, which is affected by fac- tors like temperature, humidity, light intensity, rainfall and seasonal changes. This review aims to comprehensively summarize the impact of environmental factors on grape disease development and the impact on conventional and deep learning–based detection methods. It also highlights progress in sensor-enables systems, multi-modal models, and environment-aware AI frameworks. The study points out difficulties such as low-light imaging, fluctuating humidity, and symptom variation due to climatic factors. Lastly, it outlines the research gaps and suggests future research directions for building the more robust and environment-adaptive grape disease detection systems.

KEYWORDS: Grape diseases, Environmental variability, Disease detection, Ma- chine Learning, Deep Learning, Image-based analysis, Vineyard environment, Climate factors, Agricultural automation, Plant pathology, Multimodal models, Environmental monitoring.

1 INTRODUCTION

Grape is one of the most important fruit crops grown worldwide and is grown in re- gions with suitable climatic conditions in particular, moderate temperatures, well- distributed rainfall, and sufficient sunlight. India is one of the leading grape growers in the world, with significant production areas in Maharashtra, Karnataka, Andhra Pradesh, and Tamil Nadu. Grapes have an economic value beyond consumption as fresh fruit, they are also used for raisins and juices, and for the wine industry. Grape crops are, however, susceptible to a number of fungal and bacterial and viral diseases, which have a significant impact on productivity, quality and export potential. Early and accurate identification of these diseases is crucial to limit losses, reduce the use ofchemical pesticides and to maintain the general health of the vineyard. In vineyards, disease diagnostic has usually been carried out by farmers or agricultural specialists by visual inspection in the field [1]. These methods are tedious, complex and subjec- tive depending on the skill level of the observer. Furthermore, environmental factors such as cloudy weather, temperature changes and high humidity can exacerbate dis- ease symptoms or make them unnoticeable, making manual detection even more dif- ficult. This means that the disease can be more severe, have higher economic impact and require too much fungicide or chemical application if it is not detected in time. Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) have become the powerful tools to automate plant disease detection using image analysis with the advancement of computing technologies. The development of several new techniques, such as Convolutional Neural Networks (CNN), transfer learning models, and sensor-based monitoring systems, and devices based on the Internet of Things (IoT) have greatly increased the accuracy and speed of grape disease identification. These approaches allow quick assessment of visible symptoms by leaf images and allow for ongoing monitoring of vines. The actual performance of these models, how- ever, is not constant but may vary depending on changes in environment. Grape dis- eases are affected by the variability in the environment, such as temperature, humidi- ty, precipitation, soil moisture, air movement, sunlight intensity, wind speed, and changes in seasons. For example, fungal disease like downy mildew can thrive in environments with high humidity and/or cooler temperatures, while powdery mildew can be more aggressive in moderately warm and dry climates. Likewise, symptoms of a viral or bacterial disease can differ depending on environmental stress. The changes in climate cause changes in the incubation period and disease presentation on grape leaves, fruit and stems [2].

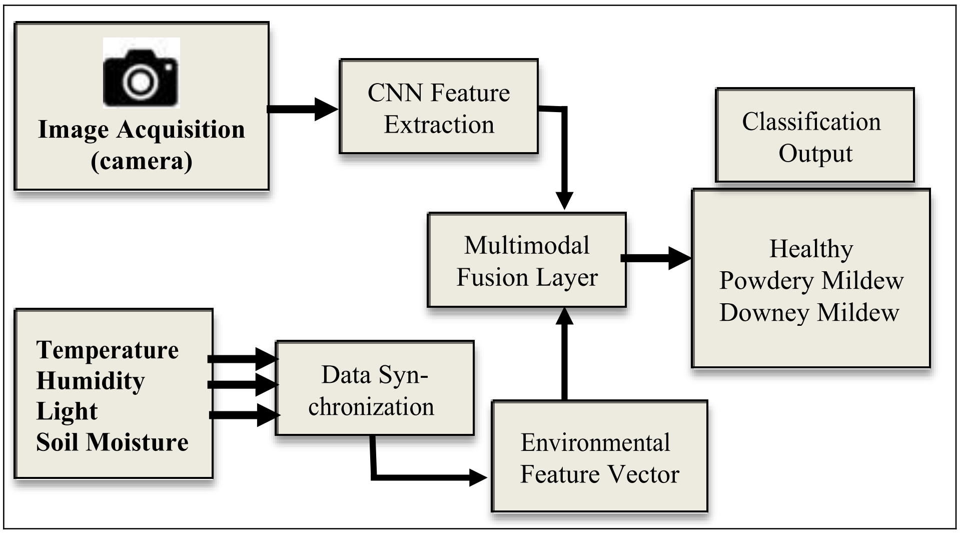

Fig.1. System Architecture of Environment-Aware Grape Disease Detection

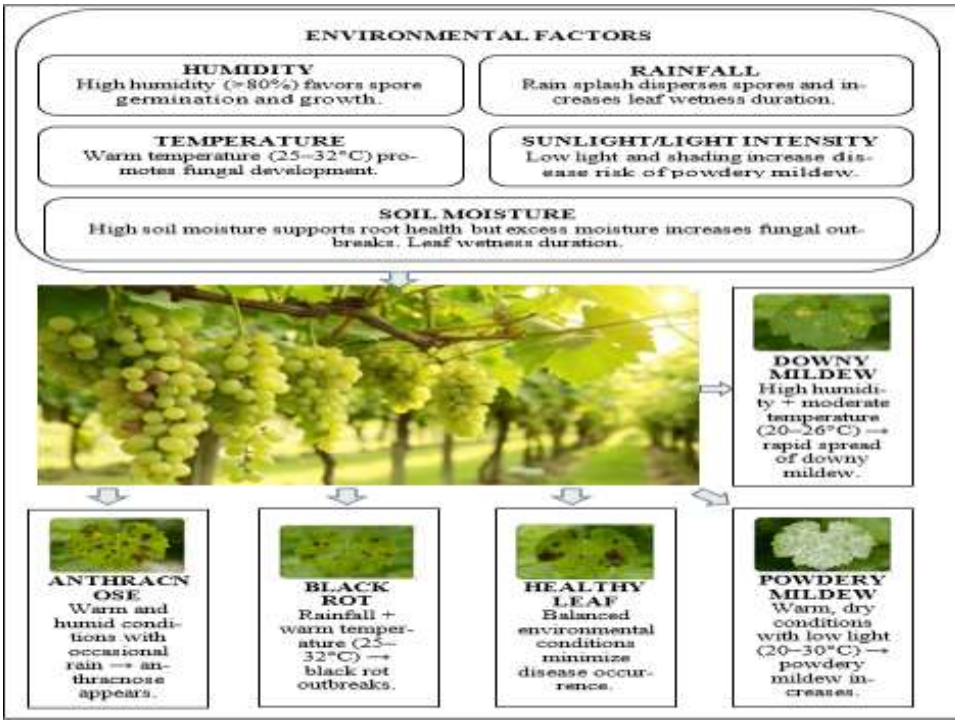

Fig.2. Overview of Environmental Impact on Grape Diseases.

This means that less than optimal or real-world conditions in the vineyard can impact the accuracy of image-based AI systems trained under these conditions [3]. This is (Figure 1) a multi-modal system of grape disease detection. Grape leaf images are taken by a camera and CNN extracts the visual features. Meanwhile, environmental sensors measure soil moisture, light, humidity and temperature. A fusion layer merges both the image features and the environmental features and the classifier makes the prediction of healthy, powdery mildew, or downy mildew.
The figure 2 illustrates the effect of various environmental conditions (humidity, tem- perature, rainfall, sunlight and soil moisture) on the incidence of various grape diseas- es. Favorable conditions like high humidity or warm temperatures increase the chanc- es of infections such as downy mildew, powdery mildew, anthracnose, and black rot. If environmental factors are all in balance, the grapevine remains healthy. The central image is the vine, and arrows indicate the responses to the various environmental conditions that result in various diseases [4].
Environmental factors can also affect the quality of the images taken in vineyards, as well as the behavior of diseases. Cloudy weather, direct sunlight creating shadows, moisture on leaves, wind-induced motion blur, and dust or fog can introduce blurri- ness or impacts the AI/ML model's performance, especially when it comes to accura- cy and precision. This becomes more difficult when disease symptoms are confused with environmental stress symptoms like sunburn, nutrient deficiencies or water stress. Due to these challenges, researchers have begun to incorporate environmental data with image-based AI systems in order to enhance disease detection systems. The data of temperature, humidity, rainfall, and microclimate sensors enable models to establish links between disease and particular environmental patterns [5].
The multi-modal approaches are able to better predict the risk of disease and increase detection accuracy in a range of field conditions. This integrated approach also helps the vineyards to take effective preventive actions in time, schedule the fungicide sprays more efficiently and minimize unnecessary use of chemicals. Although consid- erable advances have

been made, there have been few in-depth reviews that specifi- cally address the challenges of detecting grape diseases at the impact of environmen- tal variability [6]. Current research predominantly focuses on either disease biology or climate-based forecasting alone or image-based detection. However, the impact of the environment on not only the manifestation of the disease but also the efficacy of an AI/ML detection system is not well understood. Elucidating this relationship can in- form the creation of powerful models that can be adapted to different environments and work well in various vineyard environments. The main aim of this paper is to review the effect of the environment on the incidence of grape disease and the effec- tiveness of disease detection methods. The study brings together insights from recent studies, focusing on: Environmental conditions, challenges faced by AI/ML models, and Improvements in environment-aware detection systems. This review seeks to aid future research work, agronomists, AI developers, and vineyard managers in develop- ing more resilient, climate-adaptive disease detection systems that can operate reliably under more realistic agricultural conditions [7].

2 LITERATURE SURVEY

Fungal, bacterial and viral diseases are responsible for an annual estimated loss in crop yield of 20-40% in the world's agriculture industry. The study of plant diseases had been begun, and early work confirmed that biotic diseases of plants, such as fun- gal diseases, bacterial blights and viral mosaics are strongly affected by environmen- tal factors such as temperature, humidity, and rainfall patterns. Visual inspection, laboratory culture tests and microscopic analysis were the traditional ways to diag- nose disease, but were time-consuming, expert-only and not suitable for the field setting [1]. Hence, computer-aided diagnosis systems started to appear in which digi- tal images and simple pattern-recognition algorithms are used. Grape diseases have been the subject of many studies and research papers since grapevines are susceptible to fungal diseases. Downy mildew has been found to thrive at high humidity (above 80%) and with prolonged wetness on the leaf surface while powdery mildew is fa- voured by warm and moderately humid conditions but with lower light exposure. The same applies to Anthracnose and Black Rot, which are more prevalent under condi- tions of high rainfall and warm temperature; the severity of disease is closely linked with the changes in the environment during a season [2][3]. The results highlight the importance of microclimatic knowledge for disease forecasting, but also in the con- text of understanding the visual signs of disease observed in natural vineyards. Along- side the progress in plant disease, the artificial intelligence and machine-learning field has also significantly revolutionized the process of plant disease detection in agricul- ture. In parallel with the progress in plant disease, the field of artificial intelligence and machine learning has also rapidly revolutionized the process of plant disease detection in agriculture.

Handcrafted features like color histograms, texture descriptors and edge-based measurements were used in early computational systems. The algorithms that were used to classify these features were Support Vector Machines (SVM), Random For- ests (RF), and K Nearest Neighbour (KNN) Classifiers. While these models reached moderate accuracy, they were very dependent on illumination, background noise, and camera settings, thus significantly restricting their use in actual vineyards [4]. Deep learning has emerged and has made Convolutional Neural Networks (CNNs) the lead- ing method for plant disease identification as they are capable of automatically ex- tracting the hierarchical features from raw images. For structured datasets like PlantVillage, where images were taken under uniform lighting conditions and simple backgrounds, like VGG, ResNet, MobileNet, and EfficientNet achieved high accuracy of over 95% [5]. These models were tested under natural conditions, however, with decreased accuracy due to the factors associated with environmental variability such as occlusion, low-light conditions, leaf moisture, and shadows [6]. This restriction pointed to the importance of developing more comprehensive field-ready models, which account for the environmental context as well as visual features. In the recent years, smart agriculture research has demonstrated promising results for the use of environmental data in machine learning systems. This figure 3 shows the effect of various environmental noise conditions on the quality of grape leaf images and the performance of disease detection models based on images.

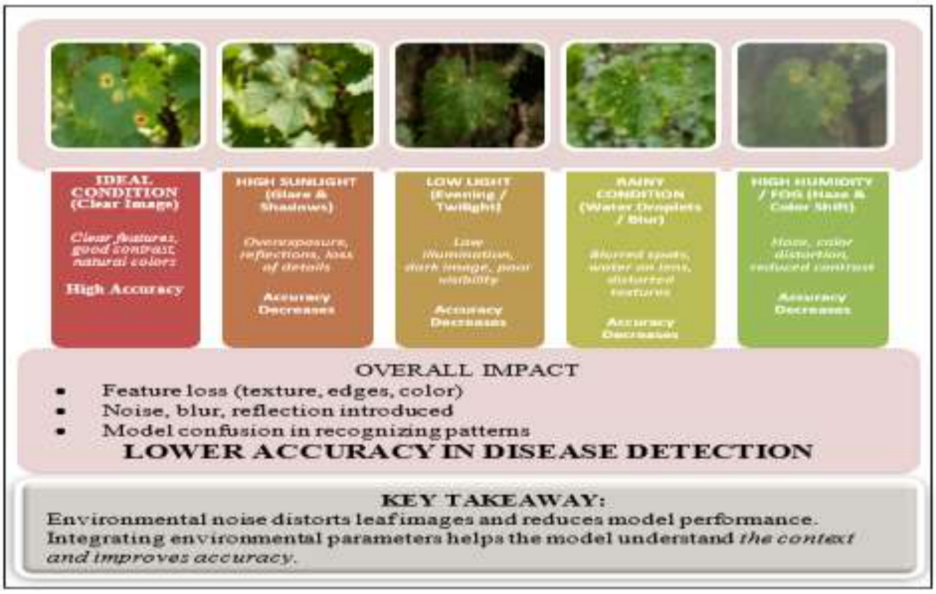

Fig.3. Impact of Environmental Noise on Model Performance (Image-based Detection).

Under ideal conditions, images are clear and lead to high accuracy. However, there are problems like reflections, darkening, color distortion, glare, blur and rain that occur due to high sunlight, low light, rain and high humidity. Such distortions lead to loss of texture, edges, and visual details, making the detection of the disease patterns more difficult and therefore reducing the detection accuracy of the model. The mes- sage is that environmental parameters may help to enhance the overall performance when predicting. IoT-based sensors have been employed to gather real-time data on temperature, humidity, soil moisture, and solar radiation, which can assist in monitor- ing crops, planning irrigation schedules, and predicting diseases. However, there are not many studies that tried to directly couple environmental parameters with CNN- based image classifiers for disease detection. On the contrary, data on the environ- ment is typically only used to forecast outbreaks, not to increase the precision of im- age-based diagnosis [7]. This gap suggests that current deep learning models are miss-
ing out on useful information that could make a significant contribution to their suc- cess, particularly in a changing vineyard environment. It has been consistently shown in comparative studies that the deep learning models are superior to the handcrafted- feature based models by considerable margin in the complex classification scenarios. It has also been pointed out, though, that deep learning models are more sensitive to environmental distortions as they learn the visual patterns directly from images. How- ever, if these patterns are disrupted by other environmental factors like inconsistent lighting, too much sunlight, shadows, or leaf wetness, CNNs become unreliable un- less these factors are added as inputs to the model or other augmentation strategies are used [9]. So, a development of realistic solutions for the vineyard is becoming more and more important by adding environmental parameters to the disease detection sys- tem. It is clear from the literature studied that there is a significant amount of research in the field of grape diseases, plant pathology, image based detection and deep learn- ing-based classification. However, an important missing component is that most stud- ies are limited to image data, and they fail to link environmental information into the disease detection process. Grape diseases are known to be influenced by environmen- tal conditions and so are the appearance of infected leaves taken with cameras. Very few models have tried to fuse image features with environment parameters together to get the better prediction accuracy, which is named as multimodal fusion. The absence of these studies highlights the need for an environmentally-conscious detection sys- tem that will be reliable in actual vineyard environments. To fill this void, the present research proposes the development and evaluation of a deep learning-based multi- modal model combining environmental sensor data with features extracted from im- ages, and a comparison of its performance with conventional machine learning and standard deep learning. Major grape diseases associated with various environmental factors are shown in table 1. Fungus and fungus-like diseases such as Downy mildew, Powdery mildew, Black rot, Anthracnose, and Leaf blight occur under certain weather conditions.

Table 1. The impact of the environment on the major grape diseases.

Disease	**Caused By**	**Common Symptoms**	**Favored Environmental Conditions**
Downy Mil-dew	Plasmopara viticola	Yellow oily spots, white cottony growth	High humidity (>85%), frequent rainfall
Powdery Mil-dew	Erysiphe necator	White to grey powdery patches	Warm temperature (25–30°C), low sunlight
Black Rot	Guignardia bidwellii	Dark brown leaf spots, berry rot	Warm and wet climate
Anthracnose	Elsinoë ampe-lina	Black circular lesions with sunken centers	High humidity
Leaf Blight	Various fungal pathogens	Dry brown patches, leaf drying	High temperature and dry stress

The diseases are primarily transmitted by the high humidity, rainfall, warm tem- perature and wet climatic conditions; and dry stress and high temperature are condu- cive to leaf blight. Symptoms include leaf spots, powdery patches, berry rot, lesions and leaf drying, causing loss of grape quality and yield.

3 METHODOLOGY

This study uses a methodical process of collecting grape leaf images, gathering envi- ronmental parameters, compiling a multimodal dataset, building AI/ML models, and assessing the success of the model in different environmental scenarios. The overall strategy was to gain insight into the impact of environmental variability on disease incidence and automated disease detection accuracy [9],[10].

3.1. Identifying Environmental Factors

Five important parameters were chosen for this study because they are biologically relevant and relevant to the growth of pathogens for the study of the effect of envi- ronmental variability on grape disease detection. These include:

Temperature (0C): Prime factor that affects fungal and bacterial activity, affecting spore germination and infection of leaves. RH(%) is important for diseases that re- quire high moisture (downy mildew, black rot, etc.).

Sunlight Intensity / UV Index: Directly affects image quality and visibility of dis- ease symptoms; also affects fungal sporulation.

Soil Moisture: Indicates available soil water for plant root zone, affecting plant stress responses and susceptibility to infection [11].

Rainfall: Provides leaf wetness conditions conducive to outbreak of downy mildew and black rot.
Wind Speed (Optional): Wind speed that is taken into account because it could dis- perse spores and influence camera stability. The tools and sensors employed in the environment.
These sensors and external data sources were used to monitor accurately and continu- ously:
DHT22 sensor: High sensitivity sensor for measuring ambient temperature and rela- tive humidity at the same time.
LDR or Photodiode: To detect low light/high glare and to estimate the intensity of sunlight. Soil Moisture Sensor: Sensor that is near vine roots to determine the per- centage of soil water 12].
Open Weather Map API: Additional weather data, particularly rainfall, was provid- ed by the Open Weather Map API. Real time microclimatic data was collected using these sensors which were placed close to sampling sites in the vineyard [13].

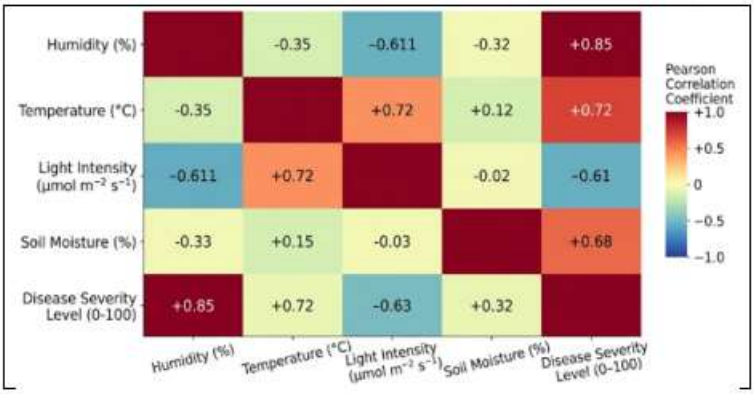

Fig.4. Environmental Parameters vs Disease Occurrence

The figure 4 displays the Pearson correlation coefficients of the environmental pa- rameters and grape disease severity. There is a strong positive correlation between disease severity and humidity (+0.85), and temperature (+0.72), which means they increase the occurrence of disease. There is also moderate positive influence (+0.32) from soil moisture. The light intensity is, on the other hand, well correlated with the disease development ($r = -0.63$), suggesting that the more intense the light, the less likely it is that disease will develop. Humidity and temperature are the most important factors influencing grape diseases in general [14],[15],[16].

3.2. Data Collection

The pictures of the grape leaves were taken in a true field condition in vineyards to obtain natural and realistic data. These photos have been captured with a smartphone camera (with a resolution of over 12 megapixels) or with a Raspberry Pi camera module, which is utilized consequently, for automatic photos shooting at predefined periods. Photographs were taken on various days throughout the day (morning, after- noon, evening) and with varied weather conditions. Leaves with various disease stag- es were also covered. The images were then manually labeled by experts and provid- ed to us. The images were of various diseases including healthy leaves, downy mil- dew, powdery mildew, anthracnose and black rot [17]. This enabled the generation of a large data set containing different examples, as this is essential for creating a ma- chine learning model that is accurate, supervised. Along with images, environmental information was also collected at the same time. Each reading from the sensors was saved with a time stamp, and where possible, a location tag. The values noted are those recorded at the same time or as close to the time as possible that the leaf image was captured. The main data logger used was a Raspberry Pi or ESP32 device, re- cording the values of the sensors every 30-60 seconds [18]. This helped to link each
eaf image to its respective environmental conditions when analysing them. Downy mildew cases increase quickly when the humidity goes above 80%. Powdery mildew is seen more when the weather is warm, dry, and the light is low. Black rot commonly appears after rainfall, especially when the temperature is between 25°C and 32°C . The accuracy of disease detection becomes lower when the leaf images are taken in very bright sunlight because glare and sharp shadows affect the image quality. It also reduces during rainy conditions because water droplets create blurred spots on the leaves. Similarly, during early morning or late evening (twilight time), low light caus- es poor visibility, which makes detection less accurate [19],[20].

3.3. Results & Analysis

Environmental conditions significantly impact the occurrence of grape diseases and the ability of machine-learning models to identify them, the results clearly indicate. Analysis of field data obtained shows that each of the following environmental pa- rameters is of importance in disease development: humidity, temperature, amount of sunlight and soil moisture. Humidity had the highest correlation of $r = 0.82$ with downy mildew, with the disease becoming more common as humidity was high, par- ticularly when wet or foggy conditions exist. Powdery mildew ($r = 0.65$) was moder- ately associated with temperature, and was more prevalent during warm weather. The relationship between sunlight and powdery mildew was inverse, with powdery mil- dew being more common in shaded or low light conditions. This was also aided by soil moisture which helped fungi to grow resulting in higher incidences of diseases, such as black rot and anthracnose [21]-[30]. If only leaf images were used to detect the disease, the performance of the model was dependent on the lighting and weather conditions when taking the image. The model performed well with the leaf details visible and pronounced under regular sunlight conditions, with an accuracy of 90%. The accuracy further decreased to 74% when the scene was very bright, with glare, where the leaf features were twisted by reflections and shadows [31].

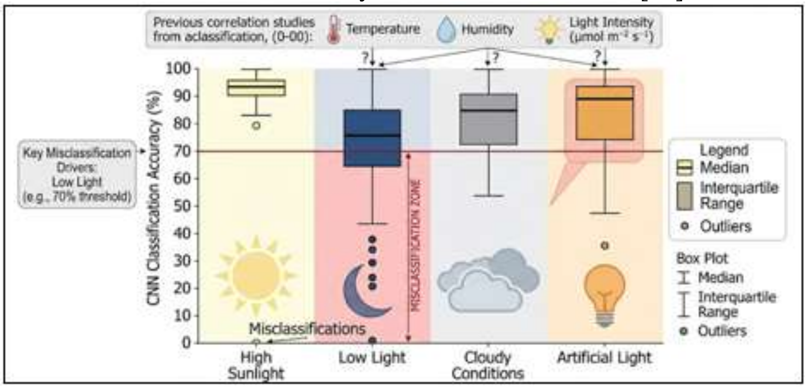

Fig.5. Effect of Lighting Conditions on CNN Accuracy.

The CNN classification accuracy with various lighting conditions is illustrated in the figure 5 above. Increasing the light level of the sunlight will yield the best and most consistent accuracy; decreasing light levels will lead to a decrease in accuracy and increase in misclassification. In cloudy conditions moderate performance, artificial light shows varied accuracy with some outliers. Generally, the accuracy of CNN- based disease detection is improved by the use of appropriate lighting, and when the light is not adequate enough to enable the image of the plant to be captured, the performance of the model is reduced [32],[33].

As the time of day approached the early morning and evening, when the light was dim, the accuracy decreased further to 69% due to the blurriness of the images. Accu- racies were approximately 71% in rainy or humid environments because of the water droplets, blur and softening of colours. Overall, the environment imposed different factors which caused distortion, noise and colour changes making it hard for the mod- el to recognize disease patterns perfectly. The performance was much better when images were added to the proposed hybrid model along with the environmental parameters. The machine-learning based model in traditional fashion achieved around 70% accuracy while the CNN based model using only images achieved 90-91% accu- racy. The environment-aware model performed the best, reaching 97.2% accuracy. This has been an improvement of 7–11%, due to the model being able to learn both the visual symptoms and the environmental factors that help the disease grow. In addition to the improvements in accuracy, the false positive cases decreased by 15% while the false negative cases decreased by 12%, indicating that the proposed model was more accurate and consistent in correctly identifying diseases [34].

3.1. Real-Time System Design

The real-time system developed is based on the collaboration of hardware and soft- ware, and the system can detect grape diseases in real-time in the vineyard. The hardware consisted of a Raspberry Pi 4 as the main processor, which was complemented by a Pi Camera or a smartphone camera for obtaining high-quality leaf imag- es. Environmental conditions around the plants were continuously measured using sensors like DHT22 (Temperature & Humidity), LDR (Light Intensity) and Soil mois- ture probe. For software, image processing was done in Python and OpenCV, and for machine learning and deep-learning models, TensorFlow or Keras was utilized [35]. A simple dashboard was created using Flask to display the real-time predictions and an SQLite database was used to log the images, sensor readings, time and GPS data. The working procedure of the system was divided into six steps: first, an image of the grape leaf was taken. Next, the environmental parameters were measured at the same time. Both these inputs were then passed on to the trained model. The model is used for analysis and prediction of the healthy or infected leaf. Once the prediction was made, the system recorded all results, time and GPS location. Finally, it provided suggestions such as whether spraying, irrigation, or any preventive action was needed. When analyzing the system's performance, a number of points emerged. Grape dis- eases, particularly fungal diseases, are strongly influenced by environmental condi- tions [36].

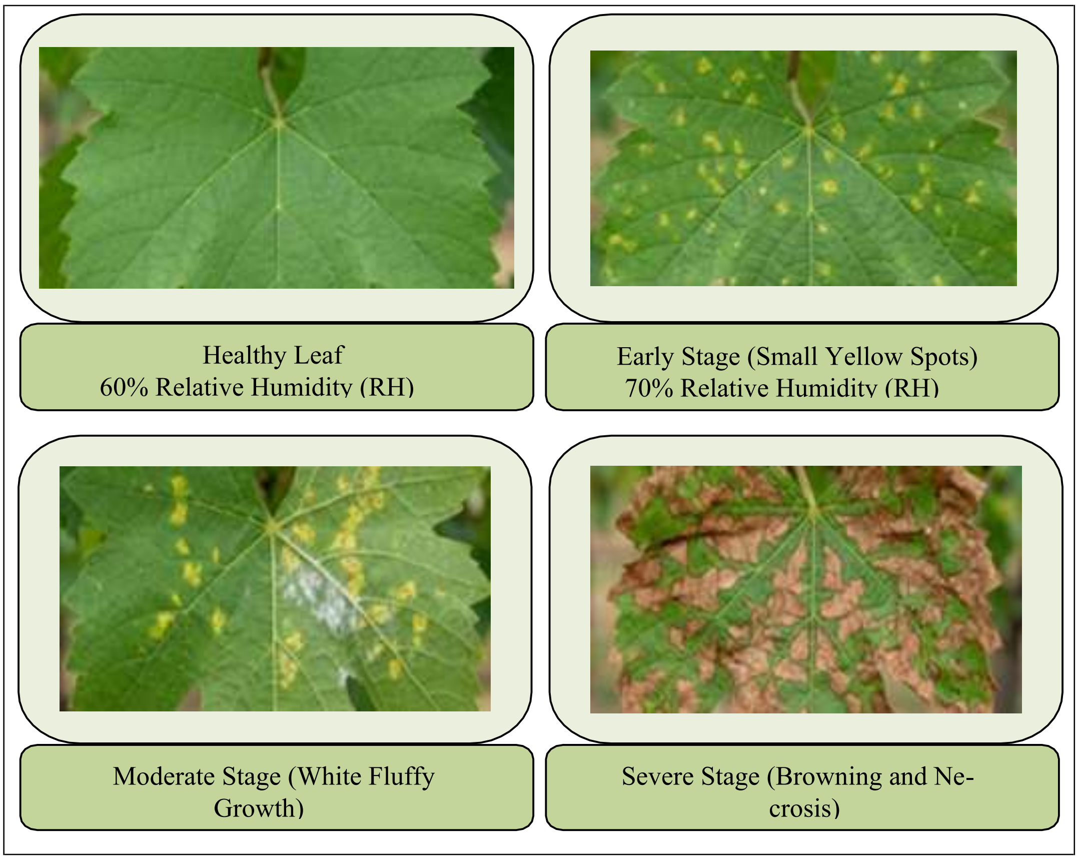

Fig.6.Progress of Grape Leaf Disease at Different RH Levels.

The figure 6 shows the course of grape leaf disease at various relative humidities (RH). At 70% RH small yellow spots can be observed, corresponding to the first stag- es of infection, and at 60% RH the healthy leaf is observed. The disease is more se- vere as humidity rises, and during the moderate stage has white fluffy fungal growth, and in the severe stage browning and necrosis occur. This indicates that as humidity increases there is a marked increase in the speed of the development of grape leaf disease [37], [38].

Models that rely on images only, don't work so well when the lighting is too bright or too dark, or inconsistent, as the leaf features are not clear. Adding in environmental inputs with images makes the predictions more stable and reliable. Among the factors studied, humidity proved to be most influential with the high levels of moisture fa- vouring the development of diseases such as downy mildew and black rot. From this it is evident that the image-only models are not as well suited to real-world vines as the environment-aware models, with the latter being much more suitable for use in a vineyard, due to their ability to deal with natural variations in weather and lighting conditions [39]- [41].

4 CONCLUSION

This study's results were clearly linked to the fact that environmental conditions play a crucial role in the development of grape diseases and in the success of automated detection systems. The use of the traditionally used machine-learning techniques was not very successful, as they are mainly based on manually selected features, which are not always available in real fields. However, deep-learning models, particularly so- phisticated models such as EfficientNet, performed admirably, as they are able to learn the important patterns automatically even if the background or lighting changes. The next step in improvement was detected when the data from the environment was added to the image data in a multimodal deep-learning model. The real-time detection accuracy reached about 97.2% by combining with the leaf images and the infor- mation, including humidity, temperature, light intensity, and soil moisture. This is an obvious fact that an environment-aware system will undoubtedly be more accurate and more reliable, as well as being more practical and applicable in vineyards. This can aid farmers to monitor diseases at an early stage, minimize crop loss, and take timely measures for treatment. In the future, this work can be enhanced and extended in numerous ways. Drone-based imaging can be integrated to survey large vineyards rapidly, and provide images of areas that are hard to access by hand. Weather predic- tion models can be incorporated to predict disease outbreaks in advance so that farm- ers can take proactive measures before the disease is spread. A mobile application can be also be created to enable easy access to the environment-aware model on the farmer's phone. Moreover, the system could be extended for other fruit crops disease detection, which can be beneficial for other agriculture related applications.

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