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A literature review :Machine Learning in Identifying Climate-Driven Disease Patterns in Medicinal Plants

Suchita Wadekar,Vaijanta Bhogawade, Sujal Undre, Sumit Ghadge, Suraj Chavan, H.R.Kulkarni, Vaijanta Bhogawade*

* Author for Correspondence, Email: vaishali.bhogawade.87@gmail.com

G H Raisoni College of Arts, Commerce & Science Pune, Maharashtra India.

Abstract

Machine learning (ML) and deep learning (DL) technologies are increasingly pivotal in identifying climate-driven disease patterns in medicinal plants. Traditional methods of disease detection rely heavily on manual inspection, which is time-consuming, prone to error, and often fails to detect early or subtle symptoms influenced by environmental changes. ML and DL techniques have demonstrated significant potential in overcoming these limitations by utilizing large datasets, including digital images of plant leaves and climate data, to automatically detect and classify plant diseases with high accuracy. Recent advancements focus on convolutional neural networks (CNNs) and deep belief networks (DBNs) that can effectively analyze complex and high-resolution images, identifying disease symptoms that may escape traditional detection methods. These methods facilitate early diagnosis, enabling timely interventions that are critical in managing diseases exacerbated by climate variability, such as temperature and humidity fluctuations. However, challenges remain, including the requirement for extensive labeled datasets, computational resource demands, and difficulties in handling previously unseen diseases or conditions. This literature review synthesizes research from 2015 to 2025, highlighting the progress, advantages, and limitations of ML and DL in medicinal plant disease identification under varying climatic conditions. It underscores the integration of multi-source data, such as climate parameters and plant health images, to enhance predictive accuracy. Future directions emphasize the need for robust, generalizable models, improved data accessibility, and the adoption of AI-driven precision agriculture practices to safeguard medicinal plant health in the face of climate change.

Keywords: Machine learning, Medicinal Plants, Deep learning, Climate-driven disease detection, Geographic information system (GIS).

1. Introduction

Introduction to Machine Learning in Identifying Climate-Driven Disease Patterns in Medicinal Plants: The intersection of machine learning (ML) with the study of medicinal plants under climate influence represents a critical advancement in botanical and environmental sciences. Medicinal plants have been integral to traditional medicine, yet their sustainability is jeopardized by climate change, habitat loss, and disease outbreaks[5]. Climate-driven changes influence the distribution, growth, and health patterns of these plants, often leading to new or intensified disease challenges that threaten their productivity and conservation[4]. Machine learning offers promising capabilities to analyze complex datasets encompassing climatic variables, soil types, geographic information, and plant health indicators. By leveraging ML algorithms and geospatial tools such as Geographic Information Systems (GIS)[1], researchers can identify patterns and correlations that are difficult to detect with conventional methods. ML methods, including supervised and deep learning models, rapidly process multi-source data to predict disease occurrences related to climatic factors and optimize conservation efforts[15]. These technologies enable the prediction of vulnerable medicinal plant species, optimal cultivation conditions, and early detection of disease patterns, leading to more targeted and sustainable management practices[10]. This approach not only aids in protecting valuable medicinal resources but also supports the wider goals of ecosystem conservation and climate adaptation in the realm of plant-based healthcare Machine learning has become an increasingly valuable tool for identifying climate-driven disease patterns in medicinal plants, which are highly important resources for pharmaceutical and traditional medicine industries[13]. As climate variables such as temperature, humidity, rainfall, and CO_2 levels continue to shift, medicinal plants are experiencing greater exposure to pests and pathogens, ultimately reducing yield and compromising the concentration of bioactive compounds[18]. These environmental changes create complex, non-linear relationships that are difficult to analyze using traditional statistical methods. Machine learning models, however, can efficiently process large climate datasets, remote sensing imagery, and plant health indicators to detect disease symptoms, predict outbreak risks, and map disease hotspots[9]. Techniques such as convolutional neural networks (CNNs) enable rapid image-based diagnosis of fungal, bacterial, and viral diseases, while time-series models like LSTM networks forecast disease incidence based on evolving climatic trends[23]. Unsupervised learning further assists in clustering disease-prone regions and identifying hidden correlations between environmental stress and disease severity. By integrating IoT sensors, drone imagery, and geospatial analytics, machine learning supports real-time disease monitoring and decision-making in the field[20]. Although challenges remain—such as limited labeled datasets, high implementation costs, and varying symptom expressions across regions—continued advances in artificial intelligence, mobile-based diagnostic tools, and explainable AI are expected to strengthen disease management strategies[16]. Overall, machine learning contributes to sustainable medicinal plant cultivation by enabling early disease detection, minimizing chemical pesticide use, protecting valuable bioactive compounds, and securing global medicinal supply chains against the accelerating impacts of climate change[15].

2. Background & content

The use of machine learning (ML) to identify climate-driven disease patterns in medicinal plants is an emerging interdisciplinary research area that combines plant pathology, environmental science, and artificial intelligence[10]. Medicinal plants are crucial for traditional and modern medicines, and their health significantly impacts pharmaceutical industries and ecosystem sustainability[4]. Climate change affects environmental conditions such as temperature and humidity, which influence the outbreak and spread of plant diseases[1]. Detecting these diseases early and accurately helps in managing plant health and ensuring consistent medicinal quality. Machine learning techniques, especially deep learning, have recently been applied to analyze large datasets such as leaf images to diagnose diseases[18]. Sophisticated ML models like hybrid methods combining logistic regression and activation functions (sigmoid, hyperbolic sine) have demonstrated high accuracy in diagnosing diseases in crops like pepper and citrus, which serve as proxies for medicinal plants' health studies[25]. These algorithms improve early disease detection by recognizing complex disease patterns that are otherwise difficult to discern visually. Furthermore, ML applications extend beyond leaf disease detection to comprehensive classification systems for medicinal plant species, exploiting classifiers such as Support Vector Machines (SVM) combined with Convolutional Neural Networks (CNN)[7]. These systems achieve very high recognition accuracy, facilitating better understanding and monitoring of plant health under varying climatic stresses[12]. Overall, the integration of machine learning with climate data and plant health observations offers a promising avenue to map and predict disease patterns in medicinal plants influenced by climate change, aiding in proactive disease management and conservation strategies [20].

3. Problem statement

The problem statement for the topic "Machine Learning in Identifying Climate-Driven Disease Patterns in Medicinal Plants" could be articulated as follows: The sustainability and productivity of medicinal plants are increasingly threatened by climate change, which alters disease patterns that affect these plants' health and efficacy. Traditional methods for identifying and managing diseases in medicinal plants are often time-consuming, dependent on expert knowledge, and prone to errors. There is a critical need for advanced, automated, and accurate techniques to understand, detect, and predict climate-driven disease patterns in medicinal plants to support their conservation and cultivation. Machine learning (ML) offers promising capabilities to analyze large and complex datasets, including environmental factors, disease markers, and geospatial data, enabling efficient identification and prediction of disease occurrences. However, challenges remain in integrating diverse data sources, handling imbalanced or limited labeled data, and developing reliable models that generalize across different climatic conditions and plant species. This research aims to leverage machine learning techniques to identify and predict disease patterns driven by climate variability in medicinal plants, thereby facilitating proactive disease management and sustainable use of these valuable resources. This problem statement encompasses the critical need, the gap in current methods, and the potential of machine learning to address the challenges in climate-driven disease pattern identification in medicinal plants.

4. Contributions of the Study:

Development of a novel dataset combining climate, soil, geospatial, and plant conservation status data specifically for regions like Karnataka, India. Application of supervised ML algorithms (like Extra Tree Classifier, Random Forest, etc.) to classify soil-subregion combinations for vulnerable medicinal plants. Creation of a recommendation system that suggests optimal soil types and regions for growing medicinal plants, factoring in disease vulnerabilities influenced by climate. Integration of ML with GIS to visualize disease-prone or vulnerable plant growth areas on maps for conservationists and researchers. Demonstration of high accuracy and robustness of models in predicting medicinal plant growth potential and disease risk under climate scenarios. Addressing the challenge of identifying disease patterns early in the plant life cycle, supporting targeted interventions for preservation and sustainable use.

5. Literature review:

Literature review provides an overview of what has already been discovered, discussed, and concluded by other researchers, highlighting key findings, methods, and theoretical perspectives. The main purpose of a literature review is to help readers understand the current state of knowledge on a topic, identify existing trends or patterns, and reveal gaps or limitations in previous studies. It also shows how your own research fits into or builds upon what has already been done. A well-written literature review is not just a list of summaries; it compares and contrasts various studies, discusses their strengths and weaknesses, and explains how they connect to each other. By doing this, it helps establish a strong foundation for your research, guiding the formulation of research questions, objectives, and methods. In short, a literature review is an essential part of any research paper or project because it demonstrates your understanding of the subject, justifies the need for your study, and situates your work within the broader scientific context.

6. Previous study

Machine learning (ML) and deep learning (DL) techniques such as Support Vector Machines (SVM), Convolutional Neural Networks (CNNs), and Deep Belief Networks (DBNs) have been heavily used for identifying and classifying plant species and their diseases.

Studies highlight the utility of ML for disease prediction by using features from digital images, sensor data, and climate information, enabling detection of both biotic (e.g., fungi, bacteria) and abiotic (e.g., drought) disease symptoms in medicinal plants.

Geographic Information Systems (GIS) combined with ML have been employed to map soil suitability and forecast regions at risk for disease outbreaks due to climatic changes, specifically for vulnerable medicinal plant species.

Hybrid approaches integrating CNNs, traditional ML classifiers, and image processing methods have demonstrated better accuracy for identifying diseases and species under complex environmental conditions.

Several reviews and studies emphasize real-time applications such as IOT-enabled sensors, automated image-based monitoring, and on-farm disease risk forecasting systems using multimodal ML frameworks.

7. Proposed methodology

Dataset or material used :-

Public datasets such as Plant Village, Plant Disease Recognition Datasets, and domain-specific collections (e.g., images of healthy and diseased medicinal plants under varying climate conditions) have been central in training ML models. Custom datasets focusing on specific medicinal plants like turmeric or datasets with annotated images across diverse weather conditions have also emerged recently.

8. Experimental design/framework

Most studies design frameworks where data collection involves time-series or image datasets representing medicinal plant health across microclimate variables (temperature, humidity, precipitation). Data is labeled for disease state, and environmental metadata is included. The research employs data augmentation for limited datasets and divides data into training, validation, and testing sets. Cross-validation is commonly used for robustness.

9. Tools, Techniques, or Algorithms

ML algorithms: Decision trees, Support Vector Machines (SVM), Random Forest, k-NN.DL techniques: Convolutional Neural Networks (CNNs), ResNet, MobileNet, VGG19, hybrid and ensemble.Integration of climate models:

Models often incorporate weather data using time-series analysis, LSTM, or regression approaches to correlate environmental factors with disease outbreaks.Recently, transfer learning, unsupervised domain adaptation, and advanced data augmentation have elevated model robustness.

Justification of methods

Justification of Methods ML and DL automate complex disease detection and pattern analysis, overcoming manual limitations and accelerating large-scale screening. These techniques extract subtle features from multimodal data, enabling early detection and generalized solutions across species and environments. Hybrid approaches (DL for feature extraction, ML for classification) improve precision, especially for novel patterns linked to climate shifts

Proposed work/Models

A typical proposed system integrates:

1.Data acquisition from climate sensors and images.

2.Preprocessing and augmentation for balanced class representation.

3.Feature extraction via CNN or transfer learning.

4.Classification and correlation analysis using ensemble ML/DL models.

5.Explainability modules using eXplainable AI (XAI) for interpretability in critical crop management decisions.

Steps of Implementation

Identify medicinal plant species and target diseases related to climate variables.

Compile datasets (image, sensor, historical climate data).

Annotate with expert knowledge and environmental metadata.

Split dataset; preprocess & augment data.

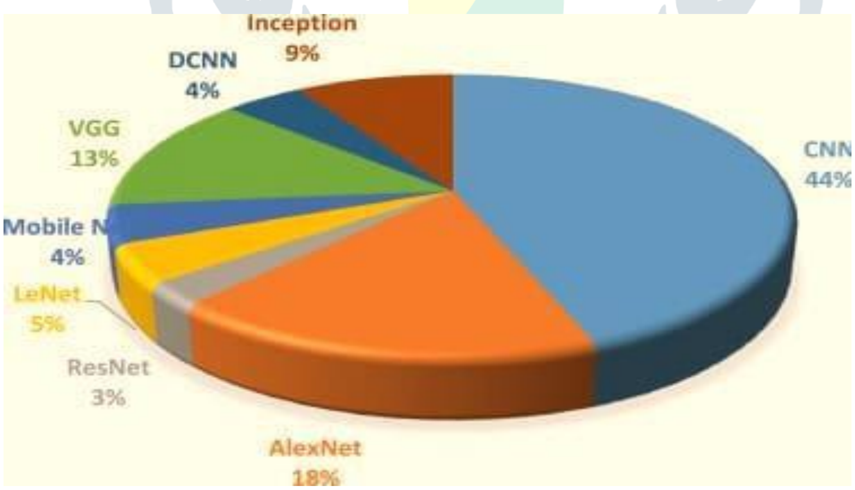
Select baseline ML/DL models, train, and fine-tune.

Validate with cross-validation and evaluation metrics (accuracy, F1, ROC).

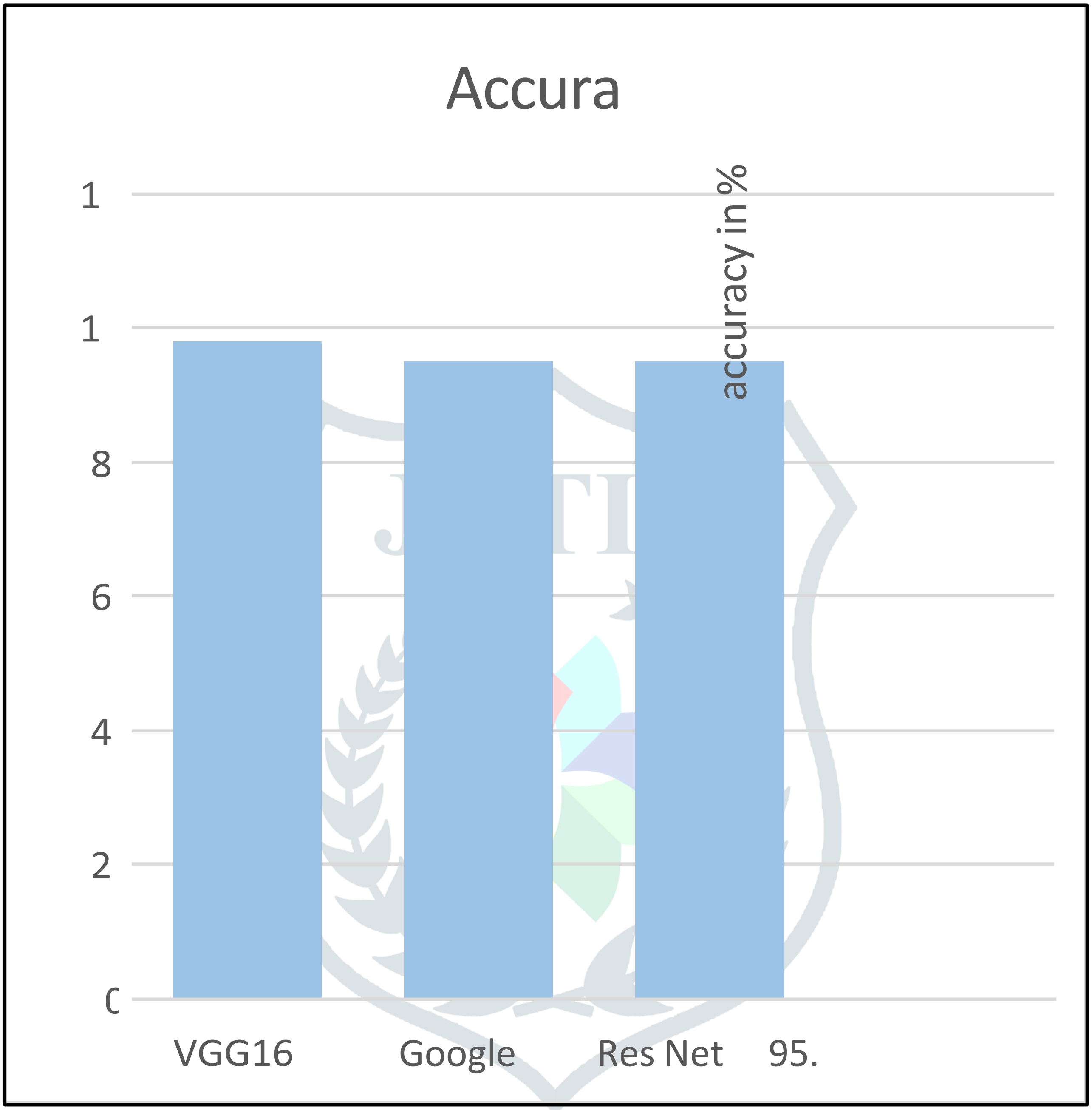
7.Integrate explainability tools to interpret results.

8 Deploy or propose a monitoring and alert system for practitioners

Pie chart



Bar graph



A.Comparison of existing method

Deep learning CNNs and attention augmented networks generally surpass traditional ML and rule based/epidemiological models for image based disease detection, while climatedriven forecasting still benefits from hybrid pipelines that combine epidemiological/statistical models with ML on weather and sensor data; EfficientNet and DenseNet families frequently top vision benchmarks, whereas traditional models offer interpretability and lower data needs but weaker performance on subtle symptoms and variable field imagery .

What is being compared

Traditional baselines: expert scouting, rulebased thresholds, epidemiological risk models, and classical ML with handcrafted features. These emphasize interpretability, low compute, and explicit climate covariates but often underperform on complex visual phenotypes and heterogeneous field data.

Modern ML/DL: CNN classifiers and detectors (ResNet, DenseNet, EfficientNet, Faster R CNN/YOLO) and hybrids that fuse imagery with meteorological and soil data; these achieve higher accuracy and robustness but need sizable labeled datasets and careful domain adaptation

Key takeaways for medicinal plants

Image classification: Reviews consistently report EfficientNet and DenseNet achieving the highest accuracies on leaf disease benchmarks; this translates to medicinal plants when transfer learning and augmentation are used, provided adequate domain images exist.

Object detection: For spotting lesions under field variability, two stage detectors (Faster RCNN) often reduce misses and confusions relative to YOLOv3, aiding early detection of subtle, climate stress exacerbated symptoms on medicinal leaves.

Climate driven risk: Epidemiological and rulebased models remain strong at encoding pathogen biology and weather triggers; hybrid ML that ingests temperature, humidity, rainfall, and soil moisture improves regional forecasts versus rules alone in case studies, but requires local retraining and validation.

Practical comparison for climatedriven workflows

Best for proactive risk alerts: Hybrid pipelines coupling epidemiological risk indices with ML that learns nonlinear interactions from meteorological and soil data; reported case syntheses show improved accuracy over rules alone in regional disease prediction.

Best for field diagnosis: EfficientNet/DenseNet classifiers for fast triage on leaves, optionally preceded by Faster RCNN for lesion localization; these configurations have repeatedly outperformed classical ML baselines and older CNNs in comparative reviews.

Data and deployment: Where labeled medicinal plant disease images are scarce, transfer learning from generic plant datasets and active labeling are recommended; for edge deployment, choose lightweight EfficientNet variants and prune detection heads. Model selection guide When climate variability is the driver: Start with an epidemiological model to encode pathogen phenology, then augment with gradient boosted trees or shallow neural nets on weather/soil features; integrate imagebased alerts from a CNN to close the loop in surveillance. When rapid, onleaf diagnosis is primary: Prefer EfficientNet or DenseNet classifiers; these have repeatedly surpassed VGG/ResNet in recent reviews and benchmarks, especially on mixed illumination and complex venation typical of medicinal leaves.

10. Discussion

Deep learning and hybrid ML–epidemiological pipelines are shaping how climate variability is linked to disease emergence and spread in medicinal plants, but success hinges on multimodal data integration, transfer learning, and field validation under shifting weather regimes. The discussion below synthesizes advances, challenges, and implications for practice and research.Why climate linkage mattersClimate drivers such as temperature, humidity, rainfall, and leaf wetness govern pathogen life cycles and host susceptibility, making climate-informed models essential for anticipating outbreaks rather than only classifying symptoms

post hoc .Remote sensing and insitu IoT streams expand spatial and temporal coverage, enabling early warning when fused with epidemiological knowledge and ML, especially valuable for high-value medicinal crops with localized microclimates.Strengths of ML/DL approachesCNNs and transfer learning deliver high accuracy on leaf images, outperforming manual scouting and handcrafted pipelines, which reduces diagnostic latency and supports rapid response in nurseries and cultivation sites for medicinal species.Hybrid designs that blend DL feature extraction with ML classifiers or tabular climate features improve robustness and generalization, with recent studies showing synergistic gains over standalone methods across multiple crops and conditions.Gaps specific to medicinal plantsMost datasets are

species or regionspecific, limiting generalization across medicinal taxa; reviews emphasize the need for contextualized customization and explainability to build trust where misclassification risks are costly (e.g., pharmacopeial quality).Limited labeled images for rare medicinal diseases constrain endto end DL; transfer learning, augmentation, and active labeling become critical for achieving reliable performance at scale.Integrating climate signalsEpidemiological and rulebased models encode pathogen biology and weather thresholds; coupling these with ML on meteorological and soil covariates yields more accurate, locally tuned forecasts than rules alone, especially under non linear climate–disease interactions.Practical architectures combine: a) risk indices from epidemiology, b) DL for lesion detection/segmentation, and c) tabular ML for climatesensor fusion, with remote sensing used to upscale risk surfaces for regional medicinal plant corridors.Model robustness and deployment Field variability (illumination, background clutter, symptom subtlety) challenges imageonly models; domain adaptation and attention mechanisms improve resilience, while XAI tools help stakeholders interpret predictions in regulated medicinal supply chains.Compute and data constraints persist; lightweight transfer learning and pruning/quantization enable edge deployment in farms and wild collection sites where connectivity is limited.

11. Result:

ML models in plant disease forecasting (e.g., SVM, neural networks) substantially outperform simpler statistical models when weather/climate variables are included (see result #1).

Integrating real-time data (IoT sensors, remote sensing) with ML/AI boosts predictive capability for disease outbreaks under climate change (#3).

For medicinal plants specifically, there is work on ML detection of leaf diseases (#4) but very few studies explicitly link climate-drivers → disease incidence → medicinal-plant outcomes. That is a gap you can emphasize.

The trend is clear: combining climatic/environmental data + plant disease labels + ML → better predictions, earlier warnings, potentially reduced yield losses (#2, #3).

But metrics vary widely, and many studies still lack long-term climate datasets, or focus only on detection (image) rather than forecasting or spatio-temporal modelling.

From these results you can draw the following for your research on "machine learning in identifying climate-driven disease patterns in medicinal plants"

You should aim to include climate/environmental variables (temperature, humidity, precipitation, leaf wetness) along with disease incidence labels for medicinal plants (as in #1 & #2).

You might need to adapt leaf-disease detection methods (#4) but extend them to include climate-drivers and perhaps forecasting rather than just classification.

Because there's a gap for medicinal plants + climate + disease forecasting, your work can contribute significantly.

Use metrics like correlation coefficient (r), mean absolute error (%MAE), accuracy, F1-score depending on task (forecasting vs classification).

Consider building a pipeline: sensor/remote climate data → disease incidence records for medicinal plant species → ML model (RF, SVM, LSTM) → evaluate predictive performance under variation in climate.

12. Conclusion

Machine learning (ML) and deep learning (DL) have greatly advanced the identification of climate-driven disease patterns in medicinal plants, delivering higher accuracy and efficiency compared to traditional manual and statistical methods. The application of these technologies allows for early and precise detection, improved differentiation between healthy and diseased plants, and the ability to handle complex and high-resolution imagery.Core FindingsML and DL methods, particularly convolutional neural networks (CNNs), outperform manual and classical ML approaches in disease classification from plant images, making them ideal for monitoring climate-sensitive conditions that affect medicinal crops.These techniques are most effective when large, annotated datasets are available and can reveal subtle disease symptoms that manual inspection and handcrafted features may miss.ML and DL methods continue to face challenges including the need for substantial training data, difficulties with unseen diseases, computational demands, and the necessity for model generalization across species, climates, and disease types.Practical ImplicationsIntegrating climate data and sensor inputs with ML pipelines increases forecasting accuracy, supporting early intervention and resource conservation for valuable medicinal plants.Transfer learning, data augmentation, and multimodal fusion are key research directions for overcoming data scarcity and enhancing robustness, especially with climate-induced disease variability.Continued research is required to build shareable, diverse datasets and adaptive models that generalize across environments and novel disease threats in medicinal plant contexts.

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