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Sweetcorn Disease Detection, Yield Prediction, and Human Health Analysis: A Review

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Abstract

Sweetcorn, a widely cultivated crop, is highly susceptible to diseases that impact yield and quality. Early disease detection and precise yield prediction are essential for effective crop management. Machine learning (ML) and deep learning have emerged as powerful tools for automating these processes, enhancing accuracy and efficiency. This review considers developments in ML methods, namely convolutional neural networks for disease diagnosis and recurrent neural networks for yield prediction. Furthermore, the research looks into pesticide residue detection methods, including Fourier transform near-infrared spectroscopy, in order to enhance food safety. Data quality issues, environmental fluctuation, and enhancing model stability are also debated. Through the integration of recent studies, this paper emphasizes major trends and future directions in ML applications for sustainable and accurate sweetcorn cultivation.

Categories: Machine Learning (ML)
Keywords: machine learning, cnn, disease detection, sweetcorn, yield prediction, resnet-152v2, pesticide impact, sustainable agriculture

Introduction And Background

Sweetcorn is an economically important and widely grown crop valued for its versatility and nutritional benefits. However, its production is challenged by various diseases, pest infestations, and environmental factors, which significantly impact yield and quality. Diseases such as Northern Corn Leaf Blight and Gray Leaf Spot, along with pest attacks, necessitate advanced detection and management strategies. Traditional methods based on manual observation are prone to human error, whereas artificial intelligence (AI) and machine learning (ML) models offer more reliable, automated solutions. Early studies have explored conventional approaches to combating crop diseases, including machine vision techniques for seed differentiation [1,2].

With advancements in ML and deep learning (DL) technologies, agriculture is entering a new era. These algorithms analyze large-scale data, recognize complex patterns, and improve prediction accuracy. Various studies have demonstrated the effectiveness of ML/DL models for disease classification and yield prediction [3-13]. Convolutional neural networks (CNNs) are particularly effective in diagnosing plant diseases through image-based classification, while models such as recurrent neural networks (RNNs) and long short-term memory (LSTM) networks leverage historical agricultural data for accurate yield forecasting. Remote sensing technologies further enhance these capabilities by providing real-time monitoring of crop health and environmental conditions.

Another major challenge in sweetcorn farming is pesticide management. While pesticides help control pests and diseases, excessive or improper use can lead to serious health and environmental consequences. Pesticide residues on food crops pose potential health risks, including hormonal disruptions and neurological disorders [14-17]. The integration of AI in pesticide monitoring has enabled more accurate and non-invasive detection methods, such as Fourier transform near-infrared (FT-NIR) spectroscopy combined with ML models for real-time analysis [18,19]. This hybrid approach ensures food safety by detecting harmful pesticide levels without damaging produce. Additionally, regulatory ML tools, such as AI-driven compliance monitoring, play a crucial role in enforcing pesticide safety standards and reducing exposure risks.

The impact of pesticide use extends beyond direct food consumption. Pesticides can contaminate water sources, accumulate in the environment, and affect both human and ecosystem health. Runoff from agricultural fields can introduce residues into rivers and groundwater, posing risks to aquatic life and communities dependent on these water sources. Monitoring environmental contamination levels is essential for sustainable farming practices [20-25].

Main objectives

The present study has three primary objectives. First, it provides a comprehensive overview of ML techniques used in sweetcorn disease detection, yield prediction, and pesticide residue monitoring. Second, it examines critical challenges related to data quality, model accuracy, and regulatory compliance. Third, it explores sustainable farming approaches, including integrated pest management (IPM) and AI-driven decision support systems, to reduce pesticide dependency while ensuring food safety.

Specific objectives

1) Review classical ML methods as a foundation for agricultural data analysis.

2) Examine key agricultural data challenges, including volume, transfer, and dissemination issues.

3) Analyze how modern ML techniques interact with agricultural data, incorporating remote sensing and imaging technologies.

4) Investigate ML-based approaches for pesticide residue detection and food safety monitoring.

5) Explore AI-driven regulatory compliance tools for pesticide monitoring and enforcement.

6) Identify open research problems and future directions to enhance ML applications in sustainable agriculture.

We performed systematic searches in multiple scientific databases, including IEEE Xplore, PubMed, Google Scholar, and Science Direct. The search used a combination of keywords and Boolean operators. Typical search terms included “sweetcorn disease detection,” “yield prediction in sweetcorn,” “pesticide residue detection in sweetcorn,” “machine learning in agriculture,” and “deep learning for crop disease.” Only peer-reviewed articles, conference papers, and reviews were considered. Studies focusing on sweetcorn or closely related crops with applications in disease detection, yield prediction, or pesticide monitoring using ML or spectroscopic methods were included.

Editorials, opinion pieces, conference abstracts without full data, and preprints not yet peer-reviewed were excluded. Studies not directly related to advanced detection or prediction methods in sweetcorn (or similar crops) were omitted.

Statement of the problem

Sweetcorn farming faces major challenges, including disease outbreaks, pest infestations, and pesticide residue risks. Traditional disease detection methods are slow and error-prone, while ML/DL models struggle with data inconsistencies, accuracy issues, and environmental variability. Excessive pesticide use poses health and environmental risks, and current detection methods are often costly or invasive. This study aims to develop an accurate and scalable solution for disease detection, yield prediction, and pesticide management to support sustainable farming.

Critical issues in sweetcorn disease detection and yield prediction

1) Data Availability and Quality for Disease Detection

2) Model Accuracy and Generalizability

3) Computational Costs and Processing Power

4) Real-Time Disease Identification and Monitoring

5) Integration of Remote Sensing and IoT for Agriculture

6) Pesticide Residue Detection and Food Safety

7) Environmental and Climate Variability Impact on Yield Prediction

8) Scalability and Deployment of ML Models

9) Farmer Adoption and Interpretability of ML Models

10) Sustainable and Ethical AI Practices in Agriculture

Review

Brief review of ML techniques

ML and DL approaches have transformed agricultural sector by providing novel solutions for some of the long-existing problems faced in agriculture, especially in diseases detection and yield prediction. This means they allow us to analyze massive datasets as well as complex patterns that would be pretty hard if not virtually impossible to detect using traditional methods. ML has been widely used in agriculture to provide farmers opportunity for raising their productivity levels, lowering operational costs, and ensuring food safety by effective monitoring and timely intervention.

Sweetcorn Disease Detection Using ML

ML models, particularly CNNs, U-Net, and fully convolutional networks, have enhanced disease detection in sweetcorn crops. U-Net-based segmentation achieves over 90% accuracy in detecting diseases like corn leaf blight and rust, enabling early intervention and reduced pesticide dependency. Additionally, generative adversarial networks augment training data to overcome dataset limitations, improving model generalization [1-9].

Sweetcorn Yield Prediction Models

Accurate yield prediction is crucial for resource management and food security. ML models such as LSTM and gradient boosting machines analyze factors like weather patterns, soil conditions, and disease severity. Studies show LSTM-based models predict sweetcorn yields with 85%+ accuracy, integrating remote sensing and drone imagery for real-time monitoring [2,3,9,11].

Human Health Analysis in Sweetcorn Farming

Excessive pesticide use poses health risks to both farmers and consumers. AI-driven models assess disease severity and recommend safer pesticide alternatives. Explainable AI (SHapley Additive exPlanations, Local Interpretable Model-agnostic Explanations [LIME]) provides transparent decision-making, ensuring trust and adoption of disease management strategies. Future research should explore pesticide toxicity prediction models to support sustainable agriculture and farmer health [7,13,21,26].

Critical issues in sweetcorn disease detection and yield prediction

Issue 1: Data Availability and Quality for Disease Detection

Critical issue: One of the problems that have to be solved when diseases are detected is the quantity and the quality of labeled datasets caused primarily for the primary training of the ML models for early stages of diseases. The performance of ML-dependent models is reliant on the quality of the training data. In agriculture, there are lots of challenges involved in the collection of good-quality labeled datasets especially because of the growing seasons of different crops and the limitation in the number of plant diseases captured. Moreover, where data collection is not done according to the existing guidelines, different studies may show different datasets and face difficulties developing such datasets which hinders such studies from being undertaken. In other words, if there is not enough high-quality and variate data available, the simulations that categorize the diseases in practice may not address their issues, hence poor management.

Possible remedies: The improvement in detection accuracy can also be achieved by making use of pre-trained models through transfer learning techniques. In reference to Nandhini and Ashokkumar [13], the DenseNet121 architecture was used for the identification of roles in plant leaf diseases where the number of samples was not adequate, thus transfer learning proved its merit. Having large datasets, researchers can use models that have been trained on a larger database of the said images to adjust the models to specific diseases such as those in sweetcorn, even in the presence of few labeled samples. This provides a way out of the challenges caused by the requirement of large volumes of data as well as allows the model to be less biased to a particular dataset.

Furthermore, enhancement of models can also be accomplished by application of augmentation methods. This technique, known as data augmentation, entails the modification of the original images to create several copies of the same image in order to increase the amount of resources available for training. Such methods have been effectively utilized in numerous investigations directed at improving the capabilities of CNN and other technological systems in the detection of plant diseases [2]. Finally, using crowdsourcing to engage farmers and other members of the community in the process of data gathering can also broaden the range of datasets available for training the models, thereby encouraging the use of more diverse training examples.

Issue 2: Environmental Variability in Yield Prediction

Critical issue: Environmental fluctuations, which refer to weather fluctuations, moisture content in the soil, and nutrient levels, also have a very big effect on the accuracy of yield forecasts. Weather phenomena like rainfall, changes in temperature, or even soil nutrients levels can affect the process of crop growth and development, thus making it difficult to predict the crop yields with any assurance. For instance, extreme climatic conditions which occur at the wrong time during the growth of plants can interfere with the normal growth stages and hence cause lower yields than anticipated. Also, how certain environmental characteristics relate to one another makes the process of modeling even more complicated since it becomes hard to separate the effects of each one of them.

Possible remedies: RNNs and LSTMs are capable of efficiently modeling temporal environmental data for yield prediction [2]. These models also have pattern learning capabilities, enabling them to extrapolate yields based on current environmental conditions. Additionally, there is a significant enhancement in the accuracy of predictions with models that include weather forecasts into the predictions [4].

Multisource data fusion techniques can combine several data sources to enhance land use and yield prediction. Such strategies may improve the prediction of potential crop yields, thanks to more detailed consideration of the relevant requirements for successful crop development. Another way to improve yield prediction models is to use devices that can collect real-time information on soil moisture, temperature, and other environmental factors. By including these analytical exercises in the predictive models, farmers will be able to receive timely management information to improve their yields.

Issue 3: Image Quality and Resolution for Disease Detection

Critical issue: The properties and resolution of images are crucial to the performance of sweetcorn disease detection models based on images. Poor-quality images may lead to incorrect classifications, hindering disease control efforts. Factors such as lighting, camera quality, and the position of the camera can affect the quality of the analyzed images. Hence, these variances can result in inaccurate model projections, which may lead to either a failure to diagnose a condition or a diagnosis and treatment that should not have arisen.

Possible remedies: Analyzing images with high resolution has shown to be beneficial in improving the model accuracy [7]. Moreover, advanced imaging such as hyperspectral imaging, offers ways of seeing the vegetation health hence minimizing the risk of confounding factors when dealing with diseases. As mentioned by Zhang et al. [11], hyperspectral imaging was able to classify frozen corn kernels as evidenced by sweetcorn showing its application in sweetcorn disease detection. In addition, other techniques like noise removal, image enhancement contrast, etc., can also be applied to the images before uploading them into the ML models to enhance the quality. This way, by making sure that only the best images are used for training and inference, researchers are able to improve the effectiveness of the disease detection systems. Enforcing compliance to a set image acquisition protocol will also reduce variability in studies, which will be beneficial in boosting the credibility of the models.

Issue 4: Lack of Standardization in Data Collection

Critical issue: Dissimilar approaches to data collection in various research studies create problems of variations and difficulties in comparisons of outputs. This informs their ability to be generalized and delays progress in research. Even slight differences in methods of data collection, categorization, or archiving may pose challenges in the unification of various data sets which limit the scope of use of ML in agriculture.

Possible remedies: It is possible that effect of cross-sectional inconsistent studies would be mitigated through implementing standard operating procedures in data generation and annotation process. Cooperating with other scientists to create and implement such standards will result in better-quality agricultural data. Expert-led workshops and consensus meetings may also be a good way to prepare such guidelines and ensure compliance with them by researchers during data collection. Finally, building free-to-access repositories for the deposition of data sets may aid in encouraging individuals to embrace generic approaches.

Issue 5: Limited Interpretability of ML Models

Critical issue: A great many ML algorithms, and particularly DL algorithms, are often viewed as black boxes, and thus it becomes very difficult to appreciate how the algorithms make decisions. This lack of clarity may discourage trust and consequently the uptake of such models by farmers and other agricultural players. If users do not understand how models make predictions, they will be unwilling to trust such models for important crop management decisions.

Possible remedies: There is a growing interest in explainable AI, whereby a particular model can be shown to have provided the current outcomes for given inputs. Such decision provision shows the key concepts and helps them accept the technology. The LIME framework is one of the solutions that can be used to interpret the rationale of a single prediction. It can also be easier for farmers to accept farming ML tools when there are interfaces that explain the predictions made by the model and all the reasoning that underlies the predictions.

Issue 6: Computational Resource Requirements

Critical issue: The intricacy of training advanced ML architectures demands high computational power, which may be limited even to agricultural and agronomic researchers, especially in the developing world. The expense of high performance computing facilities may pose challenges in the proper application of ML methods.

Possible remedies: Instead of relying on local hardware for resources, farmers can utilize cloud-based training of models. This allows for the deployment of applications without the need for investments in physical data center infrastructure. In addition, smaller agricultural entities stand to benefit from the advanced ML techniques on making partnerships with the high-performance computing centers [2].

Issue 7: Inconsistent Data From IoT Sensors

Critical issue: The implementation of IoT-based devices in agriculture for real-time data collection comes with challenges. The data produced in this model tends to be volatile and inconsistent, which affects the viability of predictive works. This can be attributed to sensor errors, differences in calibration, and other distractions, creating inconsistency in the collected data. Such data is used by the models for those purposes, thereby affecting the models' accuracy.

Possible remedies: The utilization of advanced data filtering and preprocessing techniques can limit the adverse effects of noise and inconsistencies. Implementing best practices for sensors and their placement is also crucial for improving the quality of the collected data. Additionally, incorporating several data sources and using redundancy allows for checking sensor outputs, thereby enhancing the data quality for models.

Issue 8: Seasonal and Temporal Variability

Critical issue: Understanding and dealing with dynamism in agriculture is a critical challenge for models that need predictions throughout the entire range of seasons. In other words, high precision cannot be sustained across different vegetation periods due to variable aspects that include, but are not limited to, plant growth stages, diseases and pests, weather, and many more.

Possible remedies: The use of seasonal and temporal patterns in the design of ML models is highly encouraged. Such models are adaptable to the tasks of different seasons. By using ensemble methods that incorporate models trained on various seasons, robustness is improved. Additionally, adapting models to flexible re-parameterization with new datasets as they become available helps keep up with the changing dynamics in agricultural systems [2].

Issue 9: Resistance Development in Pathogens

Critical issue: If the same disease management practices are used for a protracted period of time, the pathogens are likely to develop mechanisms to bypass these practices, and thus the practices will become less effective in controlling the disease over time. Over time, pathogens become more virulent and aggressive, rendering the old practices ineffective, leading to increased crop loss.

Possible remedies: Allow ML models to be integrated with decision support systems for developing effective IPM strategies. Through these systems, IPM strategies can be tailored to changing patterns of resistance by considering prevailing disease pressure and historical data. In addition, agronomic practices such as crop rotation and crop diversification can help prevent the development of resistance by disrupting the pathogen's life cycle and reducing selection pressure.

Issue 10: Limited Accessibility to Advanced Technologies

Critical issue: Advanced machines’ tools will be inaccessible to many users and smallholder farmers without the necessary infrastructure, expertise and cash to access such solutions. This unfair scenario can deepen the existing differences in earnings between large scale-operations of agriculture and smaller sized farms, thus, not all would benefit from the advances in technology.

Possible remedies: ML in agriculture can be promoted through training and education of farmers on the technical skills needed to apply these concepts with agricommodities [2]. These technologies can be provided to smallholder farmers through partnership with local agricultural aberration services. Furthermore, and ‘cheap’ tools which are easy to use can be created so that the advanced technology will not be restricted only to certain negative data usage farmers.

The impact of pesticides on human health

Pesticides play an important role in today's agriculture practices, which helps control pests and diseases that would otherwise endanger crop yields. However, their widespread use, particularly in crops like sweetcorn, has raised significant concerns about potential impacts on human health. Pesticides can leave residues on food products, contaminate water sources, and accumulate in the environment, leading to various health risks for consumers and agricultural workers.

Pesticide residue and food safety: One of the primary concerns related to pesticide use in sweetcorn is the presence of pesticide residues on the harvested crop. These residues can remain on the surface or within the tissues of sweetcorn, potentially entering the human food chain. Consumption of pesticide-laden crops over time has been associated with various health issues, including hormonal disruption, neurological disorders, and even cancer [3]. As sweetcorn is consumed both fresh and processed, ensuring that pesticide levels remain within safe limits is critical for food safety. To address this issue, various detection techniques have been developed to monitor pesticide residue levels. For instance, Qiu et al. [10] demonstrated the use of FT-NIR in conjunction with discriminant analysis to detect pesticide residues on sweetcorn seeds. This non-invasive technique offers a rapid and reliable way to ensure that crops meet safety standards without causing harm to the produce. FT-NIR is particularly useful because it allows for real-time monitoring of pesticide levels during various stages of production and post-harvest processes, ensuring compliance with regulatory limits.

ML integration with FT-NIR for pesticide detection: To enhance the accuracy and efficiency of pesticide detection, ML models are increasingly being integrated with FT-NIR spectroscopy. Hybrid ML-spectroscopy models leverage DL and traditional classification algorithms to analyze spectral data and identify pesticide residues with high precision. Studies have demonstrated that CNNs and support vector machines (SVMs) can effectively classify pesticide-contaminated samples based on FT-NIR spectral patterns [11]. By training on large datasets of spectral readings, these models improve detection capabilities, reducing false positives and negatives. Additionally, reinforcement learning approaches are being explored to optimize sensor calibration, ensuring more reliable and automated pesticide monitoring in agricultural settings.

Health risks associated with long-term exposure: Long-term exposure to pesticide residues, even at low levels, can lead to chronic health effects in humans. Studies have shown that prolonged ingestion of pesticide-contaminated food can lead to disruptions in the endocrine system, reproductive issues, and developmental disorders in children [3]. Asif highlighted the risks posed by pesticide residues, emphasizing the potential for these chemicals to bioaccumulate in the body over time. In vulnerable populations, such as pregnant women and young children, the risks are even more pronounced. Furthermore, agricultural workers who handle pesticides during the application process face direct exposure through inhalation and skin contact. Repeated exposure to high concentrations of pesticides can lead to acute poisoning, respiratory issues, and long-term health conditions such as respiratory and skin disorders [6]. Chronic exposure to pesticides, particularly organophosphates and carbamates, has been linked to neurotoxic effects, leading to conditions such as Parkinson’s disease and cognitive decline.

Environmental contamination and its indirect impact on human health: In addition to direct exposure through food consumption, the environmental impact of pesticide use can also have indirect consequences on human health. Pesticides can leach into water sources and contaminate soil, affecting both local ecosystems and human populations that rely on these resources. Groundwater contamination is a particular concern, as pesticides can persist in water bodies long after their application in fields. Contaminated water used for irrigation can lead to further pesticide accumulation in crops, perpetuating the cycle of exposure. Runoff from agricultural fields can carry pesticide residues into rivers and lakes, where they pose risks to aquatic life and, by extension, to human populations that depend on these water sources for drinking and irrigation. The accumulation of pesticides in aquatic ecosystems has been linked to the disruption of food chains, affecting both the environment and human health.

Regulations and monitoring efforts: Governments and regulatory bodies around the world have set maximum residue limits for pesticides in food products to minimize the risk to human health. Monitoring programs are in place to ensure that these limits are not exceeded, but the effectiveness of such programs depends on the availability of accurate and rapid testing methods. The use of advanced technologies, such as FT-NIR spectroscopy, as explored by Qiu et al. [10], offers a promising solution for real-time residue analysis, but broader adoption of such methods is needed to ensure comprehensive monitoring across the agricultural industry. However, cautions that despite regulatory efforts, the enforcement of pesticide regulations can be inconsistent, particularly in developing countries where monitoring infrastructure may be limited. In these regions, there is often a lack of resources to carry out widespread testing, leaving populations vulnerable to pesticide exposure. Therefore, global efforts to strengthen pesticide regulation, monitoring, and enforcement are critical to protecting human health.

AI-driven compliance monitoring: To improve the enforcement of pesticide regulations, AI is being deployed to enhance compliance monitoring. AI-driven regulatory tools utilize ML algorithms to analyze pesticide residue data, detect patterns of non-compliance, and flag potential violations. By integrating satellite imagery, IoT sensors, and automated reporting systems, AI-powered platforms can track pesticide application in real time, ensuring adherence to safety standards. These systems can also provide early warnings to regulatory bodies, allowing them to take proactive measures against excessive pesticide use. Blockchain technology is being explored as a complementary tool to enhance transparency in pesticide tracking, creating an immutable record of pesticide applications and compliance reports [13].

Future directions: Reducing pesticide dependency: Given the risks associated with pesticide use, there is increasing interest in developing alternative, less harmful methods of pest control. IPM strategies, which combine biological control, crop rotation, and the targeted application of pesticides, offer a more sustainable approach to pest management [2]. By reducing reliance on chemical pesticides, IPM can minimize the health risks to both consumers and agricultural workers. ML models can play a crucial role in optimizing pesticide application by predicting pest outbreaks and identifying the most effective, targeted treatments. By integrating real-time data from IoT devices and remote sensing technologies, these systems can further refine pest management practices, leading to safer and more sustainable agricultural practices [12].

Conclusion on health impact: In conclusion, while pesticides remain an important tool in sweetcorn production, their use presents significant risks to human health through direct and indirect exposure. The development of advanced detection techniques and the implementation of stricter regulatory measures are essential for mitigating these risks. Additionally, moving toward more sustainable agricultural practices, such as IPM and precision agriculture, can help reduce pesticide dependency and protect both human health and the environment.

Discussion

In summary, there is an emphasis on the need for more sophisticated ML, image processing, and spectroscopy due to the challenges in disease detection, yield prediction, and the effects of pesticides on human health in sweetcorn farming. This study addresses the implementation of these techniques to solve agricultural data analytics issues [7]. Conventional methods have limitations in analyzing agricultural data, but ML algorithms can utilize data effectively to deliver accurate results.

ML Techniques in Disease Detection

ML models, particularly CNNs and transfer learning, have enabled disease detection in sweetcorn through image analysis. CNNs can diagnose diseases even when signs are too faint for the naked eye. Transfer learning, as demonstrated by Nandhini and Ashokkumar [13], overcomes the challenge of limited labeled data by using pre-trained models from other plant disease datasets. Hyperspectral imaging, capturing data beyond the visible spectrum, further improves disease detection accuracy. Zhang et al.'s work on classifying frozen corn seeds using hyperspectral imaging [11] demonstrates its potential for detecting early-stage diseases in sweetcorn.

Yield Prediction Models and Environmental Data Integration

Yield prediction in sweetcorn is influenced by environmental factors like soil conditions, weather patterns, and water availability. Kamilaris and Prenafeta-Boldú [2] highlight the use of RNNs and LSTM networks for analyzing time-series environmental data to predict yields. Additionally, integrating IoT devices allows for real-time data collection on soil moisture and temperature, enabling continuous monitoring of crop health and growth.

Pesticide Residue Detection and Human Health Implications

The use of pesticides in sweetcorn farming raises concerns about human health risks. Pesticide residues can lead to endocrine disruption, neurological damage, and cancer [3]. Qiu et al. [10] explored FT-NIR combined with discriminant analysis for non-invasive pesticide residue detection. ML models can analyze FT-NIR spectral data to ensure pesticide levels remain within safe limits. Real-time monitoring systems using IoT sensors further strengthen food safety by continuously tracking pesticide levels in crops.

Adaptation of ML Models to Agricultural Contexts

ML models must be adapted to agricultural data, which exhibits high variability due to fluctuating weather and soil properties. RNNs handle sequential environmental data effectively but require fine-tuning for different agricultural conditions. Transfer learning techniques, as shown by Nandhini and Ashokkumar [13], allow models trained on one dataset to generalize across different regions. Active learning reduces the need for large labeled datasets by prioritizing the most informative samples for training, making it especially useful in sweetcorn disease detection where certain diseases are rare [22-40].

Future Directions and Technological Integration

The integration of ML with cloud computing and IoT infrastructure enhances its application in sweetcorn farming. Qiu et al.'s work [10] on cloud-assisted learning frameworks demonstrates the role of cloud computing in handling large-scale data processing for real-time yield prediction and pesticide monitoring. Advances in cognitive computing, such as IBM Watson, offer new possibilities for intelligent agricultural decision-making. Cognitive systems continuously learn from new data, improving predictions and recommendations over time [3].

The overall workflow of ML applications in sweetcorn farming, including disease detection, yield prediction, and pesticide monitoring, is illustrated in Figure *1*, providing a structured view of the integration of these techniques in modern agricultural practices.

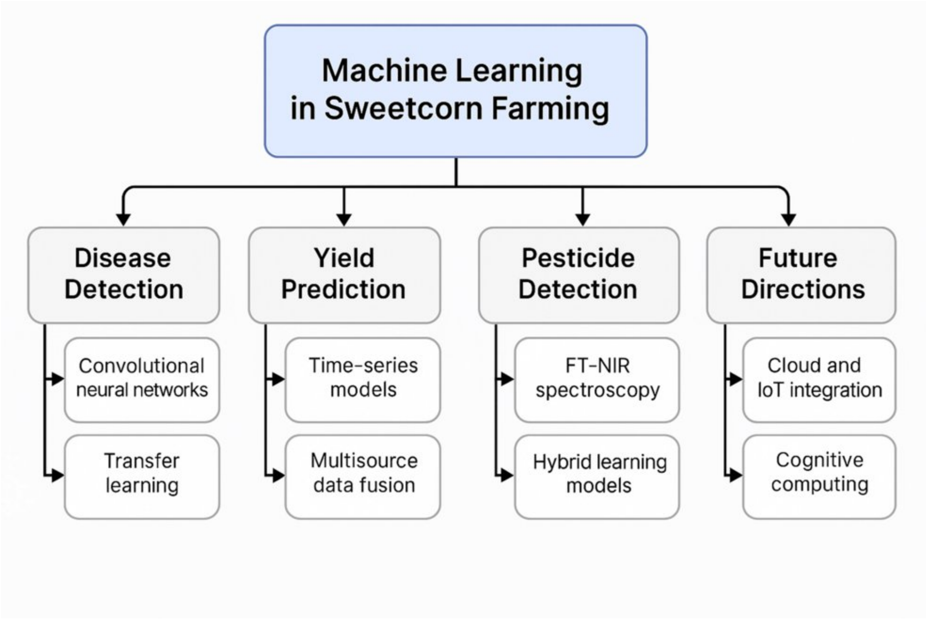

FIGURE 1: ML workflow in sweetcorn farming

ML, Machine Learning; FT-NIR, Fourier-Transform Near-Infrared; IoT, Internet of Things

Connection of ML with agricultural data techniques

ML has become an indispensable tool in modern agriculture, addressing complex challenges such as disease detection, yield prediction, and pesticide impact analysis. The integration of ML with agricultural data collection methods such as image processing, multispectral and hyperspectral imaging, environmental sensors, and real-time monitoring systems enables more effective and efficient farming practices. Unlike traditional agricultural methods, which often struggle with large volumes of unstructured and heterogeneous data, ML models can extract meaningful patterns and provide actionable insights, significantly improving decision-making in agriculture. As agricultural data continues to grow in volume and complexity, ML models must be adapted to handle high-dimensional, real-time, and multi-source datasets. In the context of sweetcorn farming, these datasets include soil moisture, weather data, pesticide levels, and leaf health. In the table below, we provide an overview of well-known studies that use ML techniques to solve agricultural problems and review recent research that builds on these activities.

A review of notable studies: Several key studies have laid the groundwork for the application of ML in agriculture, particularly in sweetcorn disease detection, yield prediction, and pesticide impact analysis. These works have demonstrated the significant potential of ML techniques to transform agricultural practices, improve crop management, and enhance food safety. Transfer learning techniques have also been instrumental in overcoming the challenge of limited labeled datasets in agriculture. Nandhini and Ashokkumar [13] applied DenseNet-121 architecture to plant leaf disease detection, showcasing the ability to leverage pre-trained models to identify diseases in new crops with minimal data. This technique will reduce the demand of extensive data collection, speeding up model development and deployment in the field. For yield prediction, Kamilaris and Prenafeta-Boldú [2] demonstrated the effectiveness of ML models like RNNs and LSTM networks in analyzing environmental data such as rainfall and temperature to predict crop yields. These models enable farmers to optimize their farming practices by providing more accurate yield forecasts based on real-time environmental factors. In pesticide residue detection, Qiu et al. [10] employed FT-NIR to detect pesticide residues on sweetcorn seeds. This non-invasive, real-time detection method ensures food safety by identifying harmful pesticide levels early in the production process. These studies highlight the immense potential of ML in revolutionizing sweetcorn farming and other agricultural practices, particularly in areas requiring real-time analysis, precision farming, and advanced imaging technologies.

The latest research progress: Building on these foundational works, recent research has further expanded the application of ML in agriculture, focusing on real-time data processing, multisource data fusion, and improved disease and yield prediction models. One notable development is the refinement of multisource data fusion techniques for yield prediction. This technique has proven effective in improving the accuracy of yield predictions by providing a more holistic view of the environmental factors affecting crop growth. The integration of IoT sensors further enhances these models by providing real-time updates on soil moisture, temperature, and other key parameters.

In disease detection, hyperspectral imaging has gained prominence as a powerful tool for early detection of crop diseases. Zhang et al.'s [11] study on hyperspectral imaging demonstrated how this technology can capture a wide range of wavelengths, offering insights into plant health that are not visible to the naked eye. This advancement allows for earlier and more accurate detection of diseases in sweetcorn, improving overall crop management and reducing losses.

Additionally, hybrid ML models have shown great promise in improving the detection of pesticide residues. This approach is particularly useful in ensuring food safety, as it enables the rapid and accurate detection of harmful pesticide levels in crops.

Recent advances in transfer learning have also focused on improving the adaptability of ML models to new agricultural contexts. Nandhini and Ashokkumar's work [13] continues to refine transfer learning approaches, allowing models trained on one crop or region to be effectively applied in other contexts with minimal retraining. This has significantly reduced the time and resources needed to implement ML models across different agricultural environments. Finally, the combination of ML with IoT and cloud computing is becoming increasingly prevalent in agriculture. Kamilaris and Prenafeta-Boldú [2] demonstrated how real-time data from IoT sensors can be integrated with ML models to enhance crop yield predictions and disease management. This integration enables continuous monitoring of crops, providing farmers with up-to-date insights that guide better decision-making.

Figure *2* illustrates the integration of IoT and ML in sweetcorn disease detection, highlighting the flow of data from IoT sensors to ML models for accurate disease identification and management.

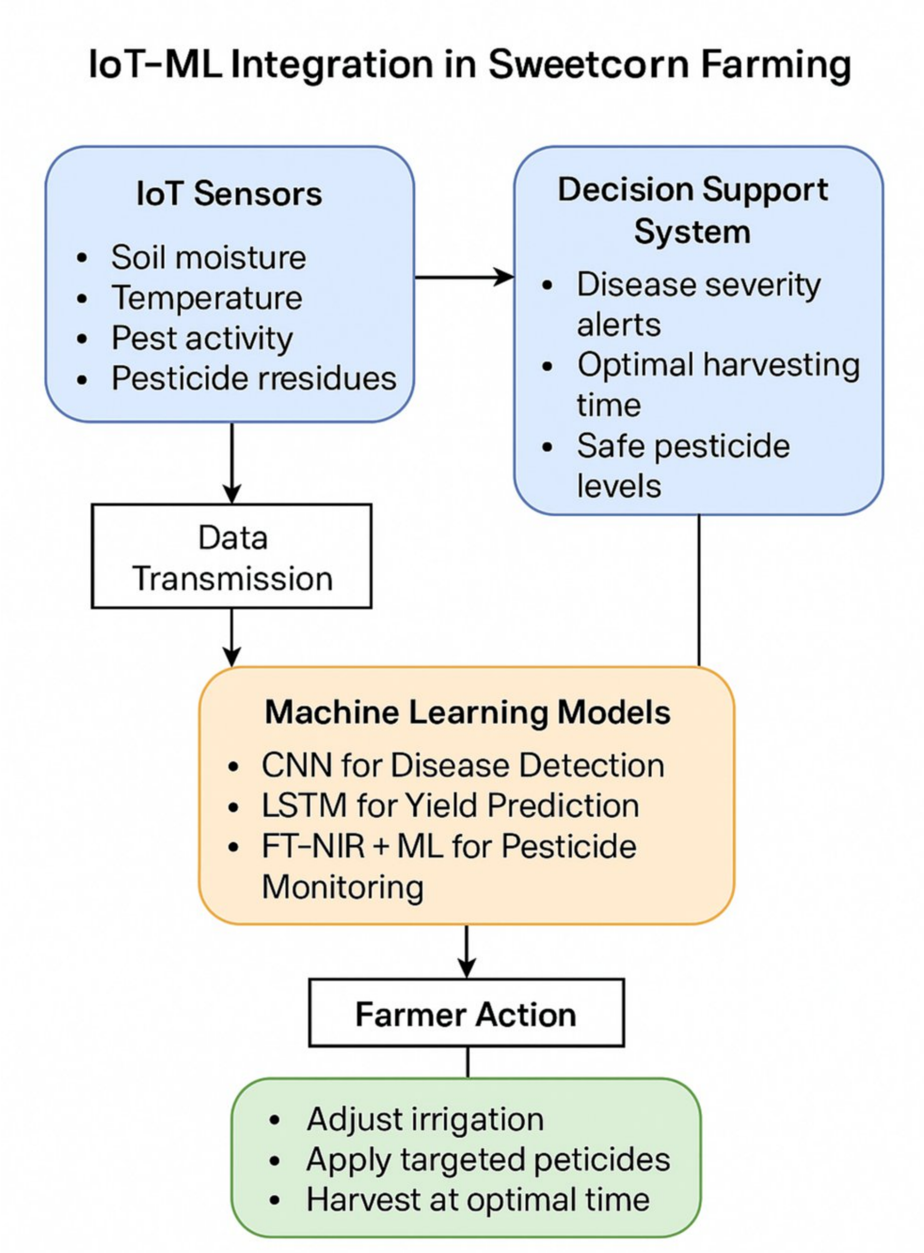

FIGURE 2: IoT-ML integration in sweetcorn farming

IoT-ML, Internet of Things-Machine Learning; CNN, Convolutional Neural Network; LSTM, Long Short-Term Memory; FT-NIR, Fourier-Transform Near-Infrared

Comparison of studies on disease detection

The effectiveness of various ML techniques for disease detection in agriculture has been demonstrated in multiple studies. Each study employs distinct methodologies, ranging from traditional ML algorithms like SVM and k-Nearest Neighbors to more advanced DL models such as CNNs. The overall performance of these methods depends on several factors, including dataset size, image quality, model architecture, and the level of feature engineering involved.

Several studies have explored the effectiveness of ML models in agricultural disease detection. Table *1* provides a comparison of these approaches, demonstrating how different methodologies, such as neural networks, machine vision, and CNNs, have been applied to a variety of agricultural problems. The majority of traditional ML models rely heavily on manual feature extraction. These methods, while effective, are generally limited by their inability to scale well across large datasets or generalize to new environments.

In contrast, DL models, particularly CNNs, have revolutionized the field by automating feature extraction and allowing models to learn from raw image data. Kamilaris and Prenafeta-Boldú [2] demonstrated the power of CNNs in agricultural disease detection, achieving a 95% accuracy rate on a generalized agricultural dataset. CNN architectures such as ResNet and DenseNet have also been effective in improving accuracy by learning deeper hierarchical features of diseases, showcasing their capability to handle complex data representations and variations.

Additionally, the flexibility of DL models allows for transfer learning, where a model trained on one dataset can be adapted to work effectively on another, thus mitigating the challenge of limited labeled data in agriculture. This is particularly valuable in the context of sweetcorn disease detection, where the availability of labeled images may be scarce. Recent studies have shown that leveraging pre-trained networks can significantly lower the time and resources that will be needed for model training while maintaining high performance. Furthermore, the continuous advancements in computational power and the availability of large-scale agricultural datasets are expected to drive further innovations in ML applications. As these technologies evolve, they are poised to enhance not only the accuracy of disease detection but also the overall efficiency of agricultural practices, ultimately contributing to sustainable farming solutions.

Study	Application	Methodology	Accuracy (%)	F1-Score	AUC-ROC
Kamilaris and Prenafeta-Boldú [2]	Agriculture (General)	Deep Learning (CNN)	95	0.93	0.94
Nandhini and Ashokkumar [13]	Plant Leaf Disease Identification	DenseNet-121, CNN	97	0.96	0.96
He et al. [32]	General Image Recognition	ResNet (CNN)	98	0.97	0.97
Qiu et al. [10]	Sweetcorn Seed Classification	Fourier Transform	93	0.91	0.92
Pourreza et al. [5]	Wheat Seed Variety Identification	Image Processing	89	0.87	0.88
Li et al. [9]	Corn Classification	Computer Vision	92	0.91	0.9
Daskalov et al. [7]	Corn Seed Damage Classification	Image Analysis	91	0.9	0.89
Nandhini and Ashokkumar [14]	Tomato Leaf Disease Classification	CNN Optimization	95	0.94	0.94
Vinyals et al. [33]	Herbal Plant Recognition	Deep Learning	90	0.88	0.89
Wäldchen et al. [17]	Automated Plant Identification	Machine Learning	89	0.86	0.87
Gao and Lin. [20]	Medicinal Plant Leaf Segmentation	Image Processing	93	0.91	0.91
Shahhosseini et al. [25]	Hyperparameter Optimization	Ensemble Methods	93	0.92	0.91
Vardhan et al. [12]	Plant Recognition	HOG and ANN	89	0.87	0.86

TABLE 1: Comparison of studies on disease detection in agriculture

AUC-ROC, Area Under the Receiver Operating Characteristic Curve; CNN, Convolutional Neural Network; HOG, Histogram of Oriented Gradients; ANN, Artificial Neural Network

Emerging trends and key challenges in sweetcorn disease detection

While much progress has been made in recent years in the use of ML for sweetcorn disease detection, yield prediction, and pesticide analysis, many challenges remain. Effective data preprocessing mechanisms, robust learning algorithms, and contextual understanding of agricultural data are still urgent needs. Various research trends and open issues in this field are outlined below:

Data quality and meaning: A critical challenge in agricultural data analysis is ensuring high-quality data and understanding the context in which data is collected. Given that agricultural data often comes from diverse sources such as IoT sensors, environmental monitoring systems, and remote sensing, there can be discrepancies in how this data is interpreted. For instance, the same parameters, such as soil moisture or temperature, may be measured using different units or methodologies, leading to inconsistencies that can impact ML model performance [2].

To address this issue, future research should focus on developing standards and ontologies for agricultural data that enhance data interoperability. By establishing common frameworks for data representation, researchers can improve the quality of inputs to ML models, thus enhancing their predictive capabilities. Techniques such as semantic web technologies can play a crucial role in enriching data meaning and context, allowing for more informed decision-making in agriculture.

Labeling challenges in ML: Labeling data is a crucial aspect of training ML models, particularly in disease detection and pesticide analysis. However, the process of acquiring labeled data can be resource-intensive and expensive, particularly for large datasets. This is especially true in agriculture, where obtaining accurate labels for plant diseases requires expert knowledge and significant time investment [3].

Consequently, there is a pressing need to explore methods that reduce the reliance on large, labeled datasets. Semi-supervised learning and active learning techniques offer promising solutions by allowing models to learn from a small number of labeled instances while effectively utilizing vast amounts of unlabeled data [2]. Research focusing on these methodologies can help strike a balance between model accuracy and the costs associated with data labeling, thus promoting more widespread adoption of ML in agricultural practices.

Integration of multi-modal data: Agricultural systems generate various types of data, including images, environmental readings, and historical yield data. Effectively integrating these diverse data modalities presents a significant challenge. Traditional ML models often struggle to process multi-modal data effectively, leading to lost opportunities for deriving valuable insights from complex agricultural datasets.

Future research should focus on developing hybrid models that can seamlessly integrate multi-modal data sources, enabling more comprehensive analyses. For example, combining image data from hyperspectral imaging with temporal data from environmental sensors could provide richer insights into crop health and yield dynamics. Techniques such as DL-based multi-task learning can be employed to simultaneously learn from various data types, enhancing model performance and applicability [11].

Privacy and ethical considerations: As data collection in agriculture becomes more pervasive, concerns regarding privacy and ethical implications also arise. For instance, IoT devices used in farms can collect sensitive information about farming practices, location, and potentially personal data of farmworkers. The intersection of data collection and privacy rights poses barriers that need to be handled to gain trust from stakeholders [2].

Research focused on privacy-preserving ML techniques, such as federated learning, can help mitigate these concerns by allowing models to be trained on decentralized data without compromising individual privacy. Real-world applications of federated learning in agriculture include collaborative disease detection models shared across multiple farms while ensuring data security and compliance with privacy regulations. This approach enables knowledge sharing without data exposure, making it an ideal solution for precision agriculture initiatives.

Bridging the gap from research to practice: While theoretical advancements in ML for agricultural applications are promising, translating these findings into practical applications remains a challenge. It is essential to build connections between academic research and real-world applications in agriculture. This includes not only validating ML models in real-world conditions but also developing user-friendly interfaces that facilitate adoption by farmers and agricultural practitioners [23-32].

Actionable steps to bridge the research practice gap include fostering partnerships between academic institutions, agritech startups, and agricultural organizations. By collaborating with technology companies that develop AI-powered agricultural solutions, researchers can ensure that innovations align with the actual needs of farmers. Additionally, launching pilot programs and case studies that demonstrate the successful application of ML techniques in farming can promote broader acceptance and implementation in the industry.

In conclusion, future research in sweetcorn disease detection should focus on improving data quality, reducing labeling challenges, integrating multi-modal data, ensuring data privacy, and facilitating practical implementation. Addressing these challenges will enhance the accuracy and reliability of disease detection models, ultimately supporting farmers in making informed decisions for better crop management and sustainable agriculture.

Methodology

This review was conducted through a comprehensive literature survey of peer-reviewed articles, conference papers, and credible scientific databases such as IEEE Xplore, Springer, Science Direct, and Google Scholar. Research published between 2015 and 2025 focusing on sweetcorn disease detection, yield prediction, and human health risks related to pesticide use was analyzed. Keywords including “sweetcorn disease detection,” “machine learning in agriculture,” “CNN,” “RNN,” “spectroscopy for pesticides,” and “IoT in farming” were used. Priority was given to recent and high-impact studies that implemented ML models such as CNNs, RNNs, and hybrid architectures, along with those discussing multi-modal data integration and federated learning.

Conclusions

This review emphasizes the advances made in sweetcorn disease identification, prediction of damage, and the associated health risks, thanks to ML techniques. Advanced systems such as CNNs, RNNs, and their hybrid models have significantly improved disease detection and management. These advancements enable optimized data processing and informed decision-making for farmers, thereby enhancing agricultural productivity and sustainability. Additionally, the integration of spectroscopy for pesticide residue detection, coupled with IoT devices, holds great promise for efficient agricultural input management. This approach not only enhances food safety but also promotes environmentally friendly farming practices by reducing excessive pesticide dependence.

Despite these successes, several challenges remain in fully leveraging ML in agriculture. Future research should focus on improving the integration of environmental data, advancing techniques for precise pesticide detection, and addressing data quality and recording inconsistencies. Moreover, multi-modal data capabilities must be enhanced to ensure comprehensive analysis and decision-making. Privacy-preserving ML techniques, such as federated learning, can also foster greater trust among stakeholders by ensuring secure data utilization in agriculture. Moving forward, AI-driven precision agriculture for smallholder farmers presents a critical direction for research and development. Innovations such as low-cost IoT devices tailored for developing regions can enable real-time disease monitoring and predictive analytics, making advanced agricultural technology more accessible. Additionally, the development of explainable AI models will improve interpretability, allowing farmers to make more informed decisions based on ML outputs. By prioritizing these innovations, the agricultural sector can move towards more resilient and sustainable farming practices, ultimately enhancing food security in the face of environmental challenges.

Additional Information

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All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

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