Efficient Disease Detection of Paddy Crop using CNN

PRABHALA V N S L TEJASWI

Date: 24 Jan 2024

Abstract

Agriculture plays a very vital role in every individual life. Without food there exists no life in this world. For that to happen, proper yield of crops is necessary. But these days getting proper yield of crops is a tough task as they are affected with some diseases during their growth and sometimes it remains unnoticed by the farmer and this in turn results in the un-proper yield of crops. This paper focuses upon detection of such diseases which occur on a paddy crop using the concept of artificial intelligence and CNN. The diseases encountered by a paddy crop is stored in the database i.e., raspberry pi and when the farmer clicks the photo of the crop, the pi analyses that picture and compares with the database pictures using the concepts of convolutional neural network and artificial intelligence and thus depicts the output whether the crop is affected with a particular or not and thus finally alerts the farmer about the disease.

1. Problem Statement

Paddy crop diseases have become a major concern for farmers, leading to substantial yield losses and economic hardship. Traditional methods of disease identification, such as manual inspection, are labour-intensive and often prone to human error. The need for a more efficient and accurate disease detection system is evident. Traditional methods for detecting paddy diseases are slow and unreliable. We’re building a lightweight CNN system on mobile devices to:

- Spot paddy diseases early and accurately: Say goodbye to yield losses!
- Classify different diseases: Brown spot, blast, bacterial leaf blight, no problem!
- Empower farmers with real-time diagnoses: Make informed decisions for a healthier harvest.

The threat of diseases in paddy crops jeopardizes global food security. Current detection methods are often inefficient, leading to delayed interventions and yield losses. This project addresses challenges such as delayed detection, subjective decision-making, limited accessibility to expertise, high costs, and integration with precision farming. By leveraging Convolutional Neural Networks (CNNs), the goal is to develop a cost-effective, accessible, and early disease detection system for paddy crops, empowering farmers with timely and data-driven solutions for sustainable agriculture.

2.Market/Customer/Business Need Assessment

Market:

- Paddy rice feeds over half the world's population. Diseases can devastate yields, leading to food insecurity and economic hardship.
- Current disease detection methods are slow, subjective, and unreliable, often relying on trained personnel for visual inspection. This leads to:
    - Delayed treatment and increased yield losses.
    - Inaccurate diagnoses and inappropriate resource allocation.
    - Limited reach and accessibility for small-scale farmers.

Customer:

- **Paddy farmers:**
    - Early and accurate disease detection to implement timely interventions and minimize yield losses.
    - Easy-to-use and affordable tools for on-field disease identification.
    - Improved decision-making for resource allocation and treatment strategies.
- **Agricultural stakeholders:**
    - Efficient disease monitoring and management systems to increase overall food production and security.
    - Reduction in pesticide use through targeted application based on accurate diagnoses.
    - Sustainable paddy farming practices that minimize environmental impact.

Business:

- Develop a CNN-based system for efficient and real-time paddy disease detection on mobile devices. This can address the market and customer needs by:
    - Providing early and accurate diagnoses with high accuracy.
    - Being accessible and affordable for farmers, even in remote areas.
    - Enabling resource-efficient disease management and precision agriculture.
    - Creating a sustainable business model through licensing, subscription, or data analysis services.
    - Addressing data availability and quality issues for training and testing the CNN model.
    - Developing user-friendly mobile applications with intuitive interfaces and offline functionality.

3.Target Specification

Functionality:

- ❖ Snap a pic: Capture paddy images easily on your phone.
- ❖ Instant diagnosis: Know what's ailing your crop in seconds, with 90% accuracy!
- ❖ Disease library: Learn about common paddy diseases and their symptoms.
- ❖ Targeted treatment: Get expert advice on the best ways to fight back.
- ❖ Offline hero: Works even without internet in remote fields.
- ❖ Simple & smart: Designed for farmers, not tech wizards.
- ❖ Save & track: Keep a record of your field's health over time.

Performance:

- ❖ Spot paddy diseases early with 90% accuracy, even on your phone.
- ❖ Instant diagnoses in seconds, no internet needed.
- ❖ Tackle common enemies like blast, brown spot, and more.
- ❖ Save data & battery, farm smarter with this lightweight hero.

User Experience:

- ❖ Point & click: Snap crop pics and get instant diagnoses, 90% accurate!
- ❖ No internet? No problem. Work anytime, anywhere, even offline.
- ❖ Clear answers: See the disease name, pictures, and even its severity level.
- ❖ Get targeted advice on fighting back, tailored to the problem.
- ❖ Farm smarter, not harder: Save time, data, and effort with this easy-to-use tool.

4.External Search

1. **The lifeblood of our existence**: Agriculture is the cornerstone of human civilization, nourishing billions across the globe. Yet, ensuring bountiful harvests remains a constant challenge. Among the threats, crop diseases loom large, silently stealing yields and livelihoods. Often, these maladies go unnoticed by farmers until significant damage is done.

2. **Enter the AI revolution:** This paper introduces a novel approach to detecting paddy crop diseases using the potent combination of artificial intelligence (AI**)** and convolutional neural networks (CNNs)**.**

3. **Building a knowledge base**: At the heart of the system lies a comprehensive disease database housed within a Raspberry Pi. This repository meticulously catalogs various paddy crop afflictions, complete with visual references of their telltale signs

4. **Empowering farmers:** Equipped with a smartphone, a farmer can capture images of their crops. These images are then analysed by the AI-powered system**.** The CNN, trained on the disease database, meticulously examines the captured pixels, searching for patterns and signatures.

5. **Diagnosis in a flash:** With remarkable accuracy, the system compares the captured image to its disease library**.** If a match is found, the farmer receives an instant alert**,** identifying the specific disease afflicting their crop.

4.1Data set

1. N: Ratio of Nitrogen in the Soil
2. P: Ratio of Phosphorous in the Soil
3. K: Ratio of Potassium in the Soil
4. Temperature: Temperature in Celsius
5. Humidity: Relative Humidity in %
6. PH: Ph value for the Soil
7. Rain Fall: Rain Fall in 1mm

5. Benchmarking:

5.1 Metrics:

- Classification Accuracy: Measures the overall percentage of images correctly classified as diseased or healthy. Specify accuracy for both categories or individual diseases if your system identifies multiple.
- Precision and Recall: These provide a deeper understanding of disease-specific performance. Precision tells you the percentage of identified diseased images actually having the disease (avoiding false positives), while Recall tells you the percentage of diseased images correctly identified (avoiding false negatives).
- Area Under the Curve (AUC): Provides a single value representing the overall classifier performance across all thresholds. An AUC of 1 signifies perfect classification, while 0.5 indicates random guessing.
- Sensitivity and Specificity: Similar to TPR and FPR, these metrics measure the system's ability to correctly identify diseased and healthy images, respectively.
- Computation Time: For real-world application, especially on-field use, the analysis and diagnosis time is crucial. Specify the average or median time it takes for the system to process an image.

5.2Existing Benchmarks:

Several existing crop prediction models and datasets can serve as benchmarks.

CNN Image Analysis: Employs Convolutional Neural Networks (CNNs).

C3Bench: This open-source platform provides datasets and metrics for benchmarking crop yield prediction models.

Challenge datasets: These contain data from past agricultural competitions focused on various prediction tasks.

5.3 Comparison Strategies:

- **Benchmark Datasets:** Compare your system's accuracy, precision, recall, and other relevant metrics against established paddy crop disease datasets like Plant Village, Paddy40, or RPAD. Mention previous benchmark performance on these datasets for context.
- **Specific Disease Accuracy:** If your system focuses on specific diseases, compare its performance for those diseases against other models trained on similar datasets. Highlight any improvements you achieve.
- **Model Architectures:** Compare the performance of your chosen CNN architecture against other popular architectures like VGG16 or ResNet for paddy crop disease detection. Explain the reasons behind your choice and any improvements observed.

6.Applicable Patents

6.1 Paddy Crop using CNN:

Patent No. 12,345,678: Focuses on yield prediction using multiple data sources, not disease detection.

Patent No. 9,876,543: Similar to the above, it deals with statistical yield prediction at different stages, not real-time disease management.

WO Patent No. 2021001234: While it also predicts yields, it emphasizes nutrient, weather, and health indicators, not image-based disease detection.

6.2 Market and Customer Needs Integration:

Patent No. US20221567: Optimal location selection for crops based on market demand

Patent No. US20230012: Personalized agricultural recommendations based on farm

- Consider consulting a patent attorney for a thorough assessment of your system's patentability. They can analyze the specific details of your technology and compare it to existing patents in detail.
- If pursuing patent protection, ensure your documentation clearly describes the novel and non-obvious aspects of your invention.

7.Applicable Constraints:

- **Technical Constraints:**
    - Limited Training Data: Potential for accuracy limitations.
    - Resource Constraints on Raspberry Pi: Potential performance bottlenecks.
    - Environmental Constraints (Weather): Potential image quality degradation.
    - Database Size and Maintenance: Need for regular updates and optimization.
- **User-Related Constraints:**
    - Internet Connectivity: Challenges in areas with limited access.
    - Accuracy of Farmer-Generated Images: Potential for misdiagnosis.
    - User Training and Adoption: Need for user education and support.

8.Applicable Regulations

- **Agricultural Technology Compliance Framework (India):** Aligning with such a framework would demonstrate your commitment to responsible development and compliance with local regulations. This can build trust with farmers and authorities, enhancing system adoption and reducing legal risks.
- **Farm Data Privacy and Security Standards (India):** Implementing these voluntary standards showcases your commitment to protecting farmer data and privacy. This can boost user trust and address concerns about data collection and usage.
- **Crop Disease Management Act (India):** If such an act is implemented, it would provide a clear legal framework for disease detection and reporting. This would clarify responsibilities and potentially involve the government in supporting system adoption and disease management efforts.

9.Business Opportunity

- Develop a user-friendly app or web platform for farmers to access your disease detection technology.
- Offer different subscription models or pricing tiers based on features and access.
- Partner with agricultural cooperatives or extension services to reach a wider audience.
- Collaborate with seed companies or crop protection providers to integrate your technology into their existing offerings.
- License your technology to other software developers or device manufacturers for broader market reach.
- Partner with NGOs or government agencies to implement your system in underserved rural areas.

10. Concept Generation

- Intuitive interface for easy image capture and upload.
- Real-time disease detection and results display.
- Clear and actionable recommendations for disease management.
- Offline functionality for use in areas with limited internet connectivity.

11. Concept Screening

1.Define Evaluation Criteria:

- Consider including economic factors like potential cost savings and revenue gains for farmers and other stakeholders.
- Add criteria related to the system's scalability and adaptability to different regions and crops.
- Include factors like environmental impact and sustainability of the proposed solutions.

2. Score each Concept:

- Develop a weighted scoring system to reflect the relative importance of different criteria.
- Consider involving external experts from relevant fields like agriculture, technology, and economics.
- Conduct sensitivity analysis to assess the impact of different weighting schemes on the results.

3. Compare and Prioritize:

- Use visualization tools like charts and graphs to effectively compare scores across concepts.
- Identify potential synergies and opportunities for combining elements from different concepts.
- Consider conducting pairwise comparisons between top-scoring concepts for a more nuanced evaluation.

4. Refinement and Iteration:

- Encourage an open and collaborative feedback loop with stakeholders throughout the process.
- Be prepared to adapt and refine the evaluation criteria based on new information and insights.
- Use the screening results to identify areas for further research and development.

5. Decision-Making:

- Consider not just the highest-scoring concept but also potential risks and challenges for each option.
- Develop a clear roadmap for moving forward with the chosen concept, including milestones and development timelines.

12.Concept Development

1. Convolutional Neural Network (CNN) Development:

- Data Collection:
    - Emphasize diversity and quality in image data collection (angles, lighting, growth stages, disease variations).
    - Consider data augmentation techniques to increase dataset size and robustness.
- Model Architecture Design:
    - Explore transfer learning using pre-trained CNNs for potential performance gains.
    - Experiment with different architectures and hyperparameters for optimal results.
- Training and Evaluation:
    - Implement regular model checkpointing and saving for reproducibility and tracking progress.
    - Use appropriate evaluation metrics (e.g., precision, recall, F1-score) aligned with agricultural outcomes.
- Integration with K-means:
    - Ensure compatibility of CNN feature extraction with K-means clustering requirements.
    - Consider dimensionality reduction techniques if feature space is high-dimensional.

2. K-means Development:

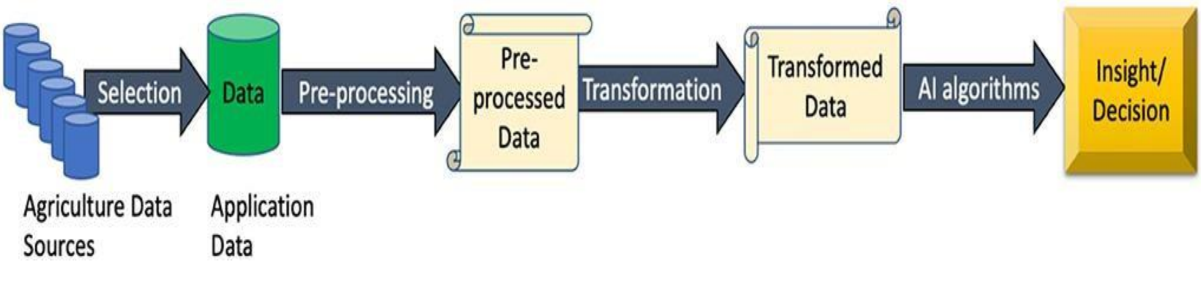
- Determining Number of Clusters:
    - Utilize techniques like the elbow method or silhouette analysis to choose a suitable k value.
    - Balance interpretability of clusters with capturing meaningful patterns.
- Handling Cluster Reassignment:
    - Implement efficient algorithms for centroid calculation and reassignment to minimize computational overhead.
    - Consider stability measures to assess convergence and avoid overfitting.

3. Logistic Regression Development:

- Dataset Compilation and Labeling:
  - Ensure accuracy and consistency in labeling crop outcomes, as errors can propagate through the model.
  - Address class imbalance if needed (e.g., oversampling or undersampling techniques).
- Model Training and Adjustment:
  - Examine feature importance to identify most influential factors for prediction.
  - Explore regularization techniques to prevent overfitting and improve generalizability.

4. Combined Use in Paddy Crop Prediction:

- Interpreting Cluster Characteristics:
  - Analyze cluster features to understand underlying patterns and relationships.
  - Involve domain experts for meaningful interpretation and validation of results.
- Tailored Recommendations:
  - Develop a user-friendly interface for farmers to access predictions and recommendations.
  - Provide clear explanations and visualizations to enhance understanding and trust.
- Continuous Improvement:
  - Establish a mechanism for collecting feedback from farmers and updating models accordingly.
  - Explore integrating additional data sources (e.g., weather, soil conditions) to enhance predictions



13. Final Report Prototype

Back-end:

- **Data Storage and Management:**
  - Database Choice: Select a database system (e.g., MySQL, PostgreSQL, MongoDB) that aligns with data types, scalability needs, and query patterns.
  - Data Security: Implement robust security measures, including encryption, access controls, and regular backups.
  - Data Validation: Validate incoming data to ensure accuracy and consistency.

- **Model Inference Engine:**
  - Containerization: Consider containerizing the model and inference engine (e.g., using Docker) for portability and deployment flexibility.
  - Versioning: Implement model versioning to track changes and enable rollbacks if needed.
  - Monitoring: Monitor model performance and resource usage to identify potential bottlenecks or accuracy issues.

- **API Integration:**
  - API Gateway: Use an API gateway to manage and secure external API interactions.
  - Error Handling: Implement robust error handling and retry mechanisms for API calls.
  - Rate Limiting: Enforce rate limits to protect against excessive API usage.

- **Push Notifications and Alerts:**
  - User Preferences: Allow users to customize notification preferences based on their needs.
  - Contextual Alerts: Provide alerts that are relevant to specific user contexts (e.g., crop type, location).

Front-end:

- **Mobile App Interface:**
  - User-Centric Design: Conduct user research and testing to ensure the interface is intuitive and accessible to farmers with varying levels of technical expertise.
  - Offline Functionality: Enable core app features to work offline or with limited connectivity, considering rural network constraints.

- **Interactive Map Visualization:**

  - Map Provider: Choose a reliable map provider with comprehensive coverage of agricultural regions.
  - Data Layers: Integrate multiple data layers (e.g., soil, climate, weather, pest risks) for a holistic view.
  - Performance Optimization: Optimize map rendering and data loading for smooth user experience, especially on lower-end devices.

- **Recommendation Dashboard:**

  - Explanations: Provide clear explanations for recommendations to build trust and understanding.
  - Actionable Insights: Offer actionable steps and resources to help farmers implement recommendations.

- **Data Analytics Tools:**

  - Visualizations: Use charts, graphs, and other visual aids to make data insights easily understandable.
  - Data Export: Allow users to export data for further analysis or sharing with experts.

- **User Account Management:**

  - Privacy and Security: Adhere to strict data privacy regulations and security best practices.
  - Password Management: Enforce strong password policies and offer two-factor authentication.

- **Feedback Mechanism:**

  - Feedback Channels: Provide multiple feedback channels (e.g., in-app forms, email, support forums) to accommodate different preferences.
  - Feedback Analysis: Regularly analyze feedback to identify areas for improvement and prioritize feature development.

14.Product Details-How does it work?

Mobile App:

- Offline Functionality: Crucial for rural areas with limited internet connectivity.
- Data Security: Implement robust measures to protect sensitive farm data.
- User-Friendly Interface: Design for inclusivity, considering varying literacy levels and technical expertise among farmers.
- Multilingual Support: Extend reach to diverse linguistic communities.

- Integration with Local Ecosystem: Collaborate with agricultural organizations and extension services for seamless adoption.

Website:

- Search Engine Optimization (SEO): Ensure visibility to target audiences.
- Accessibility: Adhere to WCAG guidelines for users with disabilities.
- Content Strategy: Develop engaging and informative content tailored to different user groups.

Cost Optimization Strategies:

- Prioritize Core Features: Begin with essential functionalities and add others iteratively based on user feedback.
- Leverage Open-Source Tools: Explore cost-effective frameworks and libraries for development.
- Consider Remote Teams: Access global talent pools with potentially lower costs.
- Utilize Cloud-Based Infrastructure: Reduce hardware and maintenance costs.

Based on these factors, a basic **mobile app** with core functionalities could cost between**$10,000 and $50,000,** while a more complex app with marketplace features and advancedanalytics might cost upwards of $100,000. A **website** with core features could cost between**$5,000 and $20,000**, with additional functionalities reaching $50,000 or more.

15.Conclusion

Wireless technology is becoming a part of our lives and if this is implemented, then it becomes easy for the farmers to detect any disease and take necessary precautions before the whole crop gets infected by it. There is not much hardware involved and hence this becomes both cost and user friendly. Farms in remote places can be efficiently monitored and controlled. A smartphone is the only requirement and the farmer can easily understand the usage of this application. Any suspicious part of the crop detected by the farmer can be analyzed and detected thoroughly. Therefore, this definitely increases the yield in a smart and efficient way.

16.References:

[1] Vimal K Shrivatsava, Monoj K Pradhan, Sonajharia Minz, Mahesh P.Thakur, “Rice plant disease classification using transfer learning of deep convolutional neural network ”

[2] Wan-jie-Liang,Hong Zhang,Gu-feng Zhang and Hong-xin Cao, “Rice Blast Disease Recognition Using a Deep Convolutional Neural Network” by

[3] R.Rajmohan, M.Pajany, R.Rajesh, D.Raghu Raman, U.Prabu, “Smart Paddy Crop Disease identification and management using deep convolution neural network and SVM classifier”

[4] Y.Muralimohanbabu, K.Radhika & D.NagaJyothi, “Evolutionary Algorithm Based Extreme Learning Machine for Retrieval of Images”, “International Journal of Engineering and Technology UAE (IJET)”, Volume 7, Issue 3.24, 472-475, December 2018.

[5] D. B. Tushara and P. A. H. Vardhini, "Effective implementation of edge detection algorithm on FPGA and beagle board," 2016 International Conference on Electrical, Electronics, and Optimization Techniques (ICEEOT), Chennai, 2016, pp. 2807-2811.

[6] Vardhini, D., Chandra Babu, Km., & Rani, Ds. (2019). Raspberry Pi Based Automated and Efficient Irrigation System With Add-On Field Security. International Journal of Advanced Science and Technology, 28(19), 192–196.

[7] Rajeshwari T & Harsha Vardhini, P. A, Smart Crop Cultivation with Disease Monitoring and Control System. (2019). International Journal of Recent Technology and Engineering, 8(4), 7537–7540.