

Agri Sure AI: Intelligent Crop Damage Assessment for Insurance Automation

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Abstract - Agriculture is seen as an essential sector for the stability of the economy while the agriculture sector suffers greatly because of the uncertainties associated with the changes in climate and the occurrence of agricultural disasters. The conventional processes that are considered for the assessment of damages to crops would involve human assessment and are known to have a number of limitations associated with the assessment processes for claims related to damages to crops that would follow. For an effective detect and quantify operation the system combines satellite pictures drone data and weather data with machine learning algorithms. As a move towards enabling the quantification of crop damage in an almost instant fashion the system makes use of image analysis and deep learning analysis of crop trends and vegetation ratios. The proposed solution makes the claim settlement process faster with less error and provides the farmer with better compensations due to the automatic nature of the crop damage assessment. This innovative solution encourages sustainable agricultural practices, which, in turn, enhances the reliability of crop insurance.

Keywords — *Crop Insurance , Deep learning, Remote Sensing , Image Segmentation , Insurance Automation , Agriculture AI.*

I. INTRODUCTION

AgriSure AI: Intelligent Crop Damage Assessment for Insurance Automation covers the basic AI-assisted method since it delves into the examination of the crop pictures which may be captured by satellites or even the cell phone and further assists in determining the health of the damaged regions provides the assessment of the damage percentage all of which are carried out by AI machine learning and computer vision. Historical crop data in addition to weather statistics are integrated to make the predictions more accurate. This method eliminates the burden of

conducting physical site visits because the final damage reports and recommendations are done automatically. This automated system reduces fraud speeds up the process of claim settlement improves transparency and ensures just compensation is paid to farmers. This can create a report for insurance automation. It is through incorporating the insurance automation technology within the insurance process of AgriSure AI that it is able to facilitate faster assessment better accuracy and clear assessment of claim payouts. This has various benefits for the farmer.

II. RELATED WORK

Any AI-driven crop damage assessment system's efficacy is mostly determined by how precisely and clearly its requirements are defined and carried out. The different user roles functional procedures and non-functional limitations that influence AgriSure AI's design and implementation are discussed in this chapter. When implemented in actual agricultural insurance settings these specifications guarantee the system's high accuracy scalability and user- friendliness.

The **AgriSure AI** platform is intended for use by various participants across the agricultural and insurance domains. Responsibilities is allotted according to the category of the user. The primary beneficiaries of the system are the farmers. The farmers access the system through the platform for the following purposes Share images of crops affected crop fields captured by smartphones and drones. Validation of insurance claims through evidence. View damage reports created by artificial intelligence Copy of claim submitted report. Farmers receive faster payments for claims and easier understanding of the process involving fewer visits to the farm. Administrators manage operations on a larger scale. User management (farmer registration surveyor accounts). Monitoring claim processing workflows. Customizing damage assessment rules based on policies. Maintaining database integrity and system security. Generating audit reports for compliance. Government / Agricultural Agencies (Optional Users) Future versions may include access for government bodies

to Monitor crop health region-wise. Plan agricultural support programs. Evaluate natural disaster impact. Functional requirements define the essential operations the system is expected to perform. These specifications represent the primary capabilities that enable the platform to carry out intelligent crop damage analysis and support automated insurance processing.

User Registration and Authentication Users (farmers surveyors administrators) must create secure accounts. Multi-factor authentication may be used for insurance officials. Authorized users can submit claims or generate reports. Image Upload Module System supports images from smartphones drones and satellite sources. Accepts various formats (JPEG PNG TIFF RAW). Performs initial validation (image quality GPS metadata timestamp). Image Preprocessing . Before AI analysis the system must Adjust brightness/contrast. Remove noise and distortions. Identify boundaries of farmland. Segment crop regions from background soil or weeds. This step enhances accuracy in damage detection

A downloadable insurance-ready report must include: Farmer details ,Crop type ,Date and time of assessment, Damage summary ,Estimated compensation range, Geo-coordinates and evidence images This report speeds up claim settlement Data is the backbone of AgriSure AI. The system requires diverse and high-quality datasets for reliable crop classification and damage detection. Drone-captured farmland images. Mobile phone images from farmers. Public agricultural datasets. Government agricultural monitoring

portals. Images of pest-infected diseased drought-affected or flood-damaged crops. vegetation index maps. Ground truth (survey reports manually labeled datasets). Using labeling tools (Labelling CVAT) images are annotated for: Crop boundaries, Damaged regions, Severity levels, Crop type categories. This labeled dataset trains AI models to recognize crop stress accurately. Before images are analyzed by AI they must be cleaned and standardized. Noise Removal: Removes blur shadows and sensor noise using Gaussian analysis by: Enhancing clarity filters. Adjusts brightness and contrast for consistent inputs.

III. METHODOLOGY

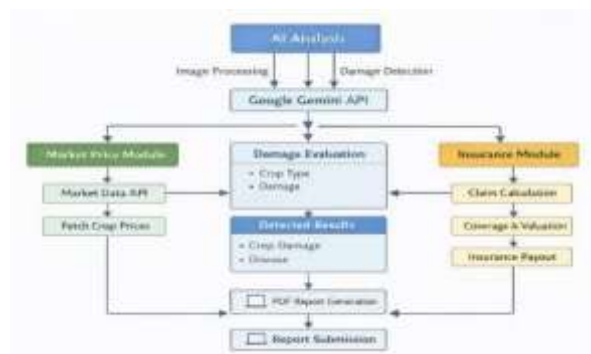


Fig.3.1: System Architecture of the AgriSure AI: Intelligent Crop Damage Assessment for Insurance Automation

AgriSure AI is structured as a multi-layered intelligent and service-oriented system. A layer does specific functions and all work together in harmony to achieve an accurate assessment of crops and automated insurance processing. From the perspective of the system it enables understanding of all the different modules working together. Farmers surveyors and insurance

administrators interact with the system through this front-end interface. Web Facilitates users to trace claims view reports and upload cropped photos. Upload Image Module: Accepts images from drones mobile and satellite. View results analytics visualized results and claims status. This is due to the fact that the core operational layer is the one in which the entire logic of the system in particular is processed.

Image Preprocessing Unit. Prepares images for AI

removing noise

Identifying region of interest (ROI). Extracting geotags and metadata. Convolutional Quantifies the damage by Pixel-based area computation Classification of damage severity Estimation of total loss percentage Report Generator. Generates automated structured reports containing: Damage summary, Loss percentage, Images with annotations, Geo-locations, Suggested compensation ranges. These reports are insurance-ready and reduce human involvement. A well-designed database ensures efficient data handling and secure storage. User profiles, Crop images and metadata, AI assessment outputs, Insurance claim records, Historical crop data .

Technologies Used: MySQL / PostgreSQL for structured data , Cloud storage buckets for images, GIS database support for map-based data. Ensures

data transfer between frontend backend and AI modules. RESTful APIs, JSON/XML data formats, Secure HTTPS protocol. Maintains smooth communication between modules enabling real- time processing.

Given the sensitivity of insurance data strong security is mandatory. User authentication , Role-based access control (RBAC) Encrypted data transmission , Automated fraud detection alerts.

The final stage of the architecture involves **PDF Report Generation and Report Submission**. All assessment results, including crop type, damage details, valuation data, and calculated insurance payout, are compiled into a structured, insurance-ready digital report. The generated report can be directly submitted to insurance authorities for approval, thereby streamlining the entire claim lifecycle. Overall, the proposed architecture provides an end-to-end automated solution that transforms raw crop imagery into validated insurance claim documentation. By integrating AI- based damage detection, real-time market valuation, and automated insurance processing within a single framework, the system enhances efficiency, transparency, and scalability in agricultural insurance management.

IV. RESULT AND DISCUSSION

Fig.4.1 presents the unified operational interface of the proposed AgriSure AI framework, demonstrating the complete pipeline from AI-based visual crop damage detection to automated insurance claim approval and financial estimation. The figure consolidates analytical outputs, severity metrics, causation analysis, and policy-based decision logic into a single structured dashboard,

thereby illustrating the real-world applicability of the proposed architecture.

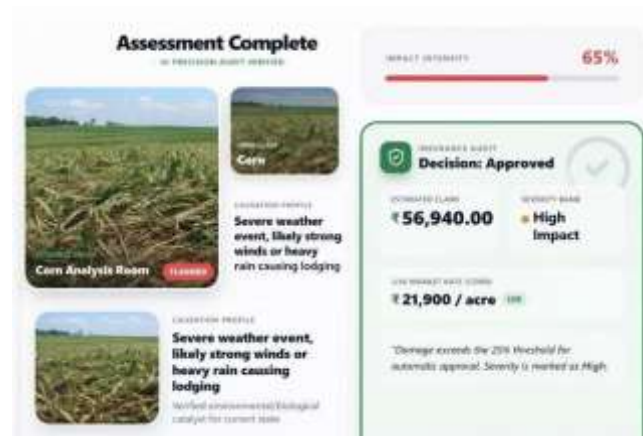


Fig. 4.1 Presents the AgriSure AI dashboard for a high- impact corn crop damage case

The upper segment of the interface displays the system status message —Assessment Complete – AI Precision Audit Verified, indicating that the uploaded crop image has successfully undergone preprocessing, feature extraction, classification, and validation stages. The AI engine performs convolutional neural network (CNN)-based image analysis to identify the crop class as corn and detect lodging damage patterns characterized by bent stems and flattened vegetation structures.

Overall, Figure 4.1 validates the effectiveness of the proposed architecture in transforming raw agricultural imagery into structured financial outcomes. The seamless integration of computer vision, market analytics, and insurance automation within a unified dashboard demonstrates the practical feasibility of deploying AI-driven crop damage assessment systems in real-world agricultural insurance ecosystems.



Fig.4.2 Presents the AgriSure AI dashboard for a low impact wheat crop damage case.

Fig. 4.2 illustrates the integrated output dashboard of the proposed AgriSure AI framework for a low-damage crop assessment scenario resulting in claim rejection. The figure demonstrates the end-to-end workflow from AI-based crop classification and damage analysis to automated insurance decision generation. In this case, the system identifies the crop class as wheat and verifies the assessment through an AI precision audit mechanism. The visual evidence panel presents the uploaded field image, which undergoes preprocessing and convolutional neural network (CNN)-based analysis to detect structural patterns and vegetation consistency

V. CONCLUSION

This paper presented **AgriSure AI: Intelligent Crop Damage Assessment for Insurance Automation**, an integrated artificial intelligence-driven framework designed to modernize traditional agricultural insurance systems. The "AgriSure AI: Intelligent Crop Damage

Assessment for Insurance Automation" Demonstrates how AI may renovate and reshape the agricultural insurance market. The system involving the integration of the high-quality image processing deep-learning models and automated report generation is fulfilling the primary objective which is the fast precise and automatic assessment of crop damage. The conventional method of crop assessment requires numerous visits by agricultural officers which is time-consuming. This is therefore where AgriSure AI comes in with its transparent and unbiased crop assessment service. The system will be capable of identifying the damaged area as well as determining crop stress within seconds using drone Satellite and MOBILE images.

Even though the system is doing outstanding work a great starting point for improvement is as follows: Datasets real-time tracking multiple crops and connection with agricultural networks. These will make the system much better.

In the end it is a great example to have AgriSure AI. Great technology that can bring a significant impact to the agricultural and insurance industry through the use of Artificial Intelligence. The technology holds speed accuracy transparency and scalability making a huge difference in ascertaining fairness and timeliness regarding crop insurance to the farmer. Currently AgriSure AI has the ability to receive periodic imagery uploads via drones smartphones and satellite snapshot updates. The technology can bring a significant impact to the agricultural industry because it managed to change the traditional crop assessment process.

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