Detecting Insurance Fraud: A Study on Field Fires with Computer Vision and IoT

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Abstract – The article suggests an automated system for overseeing the fraud detection process related to insurance claims for field fires in agriculture. This innovative solution combines computer vision, deep learning, and the Internet of Things (IoT) to leverage the strengths of each technology. As far as our knowledge extends, such an integration of these technologies has not been previously employed for analyzing insurance fraud in agriculture. The model actively monitors input from IoT devices equipped with infrared and temperature sensors. When these sensor values surpass predefined thresholds, the IoT device captures images of the field. These images are then processed by a fire detection model trained with various classifiers, allowing for performance comparisons. The reported results indicate an impressive accuracy of 97%, with potential for further improvement through a refined dataset specifically tailored for fraud detection.

Keywords — Insurance fraud detection, Agriculture, Computer vision, Deep learning, Internet of Things (IoT), Fraud analysis

I. INTRODUCTION

The agricultural sector plays a pivotal role in the Indian economy, contributing approximately 13% to the annual Gross Domestic Product (GDP) and employing a significant portion of the country's workforce [1]. Despite its importance, the sector faces risks, mainly from natural events like floods, droughts, and field fires, leading to financial distress for many farmers. In an effort to provide financial security, the Government of India has introduced various agricultural schemes, including the Pradhan Mantri Fasal Bima Yojana (PMFBY), aimed at insuring farmers against natural calamities[2]. However, historical schemes have often favored affluent farmers, and fraudulent claims have been a persistent issue.

The technological advancements of recent decades, including artificial intelligence, big data, and others, have revolutionized various industries, and agriculture is no exception[3]. Technologies such as machine learning, computer vision, and the Internet of Things (IoT) have significantly impacted different aspects of agriculture, ranging from smart irrigation to IoT devices for post-harvest loss reduction[4]. Despite these advancements, field-fire-based insurance claims have not been adequately explored.

The proposed solution leverages machine learning, computer vision, and IoT to automate the authentication of field-fire-based insurance claims, addressing a gap in the existing technological applications in agriculture[5]. Machine learning, a subset of artificial intelligence, is employed to analyze datasets and make predictions based on learned patterns[6]. Computer vision, an interdisciplinary field, mimics human vision to extract knowledge from digital images and videos. IoT facilitates communication among interconnected machines without human intervention, involving sensors, actuators, and communication links[7].

The article introduces a novel approach, combining deep learning for field detection, the Histogram of Oriented Gradients (HOG) algorithm for image processing, and Logistic Regression as a classifier for fire detection[8]. The proposed model achieves a high accuracy of 97%. Additionally, an IoT-based solution is presented to monitor the environment, aiding in the identification of fraudulent claims[9]. This comprehensive approach integrates deep learning, computer vision, and IoT, making it a pioneering effort in fraud identification within the agricultural sector[10].

II. RELATED WORK

A Convolutional Neural Network (CNN) is a deep learning algorithm specifically crafted for digital image processing. It assesses input images, giving significance by extracting weights and biases associated with distinct objects within the image. Particularly well-suited for precision-centric tasks with extensive datasets in computer vision, CNN prioritizes accuracy over speed [3]. CNN has become a fundamental component in deep learning systems for image processing. Various CNN architectures, such as U-Nets have undergone evolution over the years[11]. U-Nets, designed for image segmentation, yield higher-resolution outputs for the same input compared to traditional CNNs.

The Histogram of Oriented Gradients (HOG) is a widely embraced feature extraction method for image classification and recognition, devised by N. Dalal et al. in 2005 [6]. HOG computes centered horizontal and vertical gradients without smoothing, partitioning the input image into cells and overlapping blocks of a predetermined size[12]. The algorithm calculates gradient orientation, generating histograms for each block, which are subsequently concatenated for the entire image. HOG effectively condenses pertinent image information, streamlining learning for machine learning algorithms [13].

The heightened occurrence of natural fires, particularly forest and field fires, results from environmental degradation due to human activities, contributing to global warming and shifts in temperature [14]. Wildfires impact the environment by emitting CO2, intensifying the greenhouse effect. Amid wildfires, alterations in humidity levels and atmospheric temperature unfold, with relative humidity plummeting to 40% or less [15]. Researchers [16] have scrutinized flame temperatures and horizontal temperature gradients in wildfires, unveiling that the base temperature can soar to 1,472°F, discharging considerable energy.

Computer Vision has garnered widespread popularity and diverse applications, encompassing agriculture. It is employed for disease identification in plants [17], categorizing fruits and vegetables, and deploying Machine Learning algorithms like Linear Regression to grasp the correlation between burn severity and the burnt area [18]. Research has delved into fire colors to minimize false positives, refining fire identification. In agriculture, computer vision is instrumental in mapping crop fields, considering interconnected features and distinctive crop colors. While existing research has addressed forest fire detection, extending these techniques to crop fires necessitates further exploration. The ongoing work in computer vision for crop fires is in its preliminary stages, underscoring the imperative for more comprehensive research

III. METHODOLOGY

Semantic Segmentation is a process that involves assigning class labels to individual pixels in an image, essentially identifying distinct objects within the image. This image processing technique has been automated through the utilization of Convolutional Neural Networks (CNN) and other machine learning algorithms. The proposed approach employs Semantic Segmentation to discern crop regions in a field image by utilizing a U-net architecture designed for the analysis of 500 x 200 RGB images extracted from a satellite view of the field regions

In the realm of classification, a supervised learning technique, the proposed work employs four classification methods—Logistic Regression, Support Vector Machines (SVM), K-Nearest Neighbours (KNN), and Naive Bayes. These techniques are compared for their accuracy in fire detection. Logistic Regression utilizes a sigmoid function and performs optimally in models with two classification classes [5]. Support Vector Machines segment points and classify them using a hyperplane [10], while K-Nearest Neighbours operates on numerous classification types by dividing and using centroids in iterative cycles to classify each type [12]. The Naive Bayes algorithm, based on Bayes theorem, applies probability for the classification of multiple classes [18]. Each algorithm has a distinct underlying approach, and their performance is compared on the same dataset to determine the most effective technique for the given problem.

Sensors play a pivotal role in any IoT-based system, responsible for gathering environmental information. In the context of wildfires, essential variables include relative humidity, atmospheric temperature, and the infrared (IR) footprint of the fire. The proposed work integrates these variables into decision-making and fraud detection through rear sensors.

As the proposed work is unique, a pre-constructed dataset was not available. The dataset for mapping field regions using Semantic Segmentation was self-developed by editing airborne images of agricultural fields, extracted from existing satellite images. The dataset for fire and smoke detection was constructed from drone video feeds of burning fields. High-quality videos with a resolution of 720 pixels were obtained, and frame extraction was performed per second. The extracted images were resized to a maximum height of 199 and a maximum width of 500.

The proposed model utilizes U-Nets for Semantic Segmentation, HOG for feature extraction, and various classification algorithms (Logistic Regression, SVM, KNN, Naive Bayes) for fire detection. An IoT-based system is employed to identify fire initiation, record temperature and humidity variations, and further analyze the data. The implementation involves mapping insured field regions, recording temperature and humidity, detecting fire initiation using the IoT device's IR sensor, capturing drone images or videos of the mapped field regions, using classifiers for fire detection, and combining the outputs with mapped field regions and sensor data to verify the validity of insurance claims.

IV. RESULTS

The proposed model underwent training using a custom dataset comprising 1715 images depicting agricultural fields with and without fire for classification purposes. This dataset was partitioned into a 70:30 ratio for training and testing. The application of Histogram of Oriented Gradients (HOG) on the images yielded 7991 features, and a subset of these features was selected for input into the classifiers for subsequent classification. The identification model demonstrated accurate results in detecting fires in agricultural fields. Consequently, integrating the models for semantically segmented satellite crop fields and fire detection could lead to the development of an insurance fraud detection system specifically targeting the destruction of agricultural fields by fire. The outcomes obtained from the four classifiers contribute to this comprehensive understanding and set the foundation for further research and practical applications in the domain.

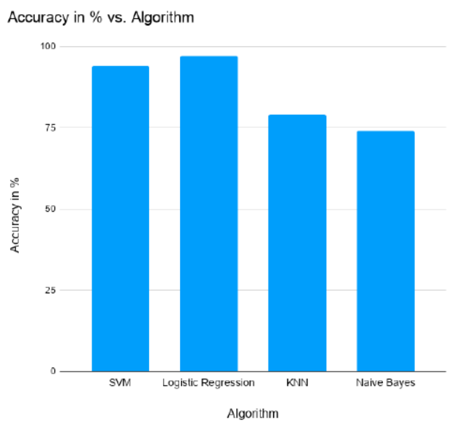

Fig 1: Accuary obtained from different classifiers

V. CONCLUSIONS

The article introduces an innovative method for analyzing field fires, particularly for identifying fraudulent insurance claims. The proposed model underwent testing with four classifiers – Logistic Regression, KNN, SVM, and Naive Bayes – and demonstrated its highest accuracy with Logistic Regression at 97%. Enhancing the system's accuracy can be achieved through the inclusion of extensive and diverse datasets related to burning field images, leveraging the improved detection capabilities of computer vision systems with increased data volume. Additionally, the proposed approach could benefit from a more in-depth exploration of agricultural field fires in India, potentially yielding more specific outcomes. Introducing advanced technologies such as quantum computing and deep learning could further enhance the system's performance and resilience to noise. Moreover, the amalgamation of the technologies employed in this system holds promise for applications beyond fraud detection and agriculture

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