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X^{th} Semester Minor Project/UG Research Work-X

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Department of DSAI

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CERTIFICATE

This is to certify that the project titled “Geolocation Based Crop Identification And Area Mapping” by “Mr.Kumar Gaurav Atram” has been carried out under my/our supervision and that this work has not been submitted elsewhere for a degree.

(Signature of Guide)

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December, 2025

Declaration

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Geolocation Based Crop Identification And Area Mapping

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***Abstract*—Accurate identification of crop types and precise estimation of cultivated area are essential for effective agricultural planning, yield forecasting, and resource management. This project presents a geolocation-based crop identification and area mapping system that integrates deep learning–based classification with advanced image segmentation techniques. For crop type prediction, a gated fusion model combining ResNet and Scale-Invariant Feature Transform (SIFT) features is employed. ResNet extracts high-level semantic representations from satellite or aerial imagery, while SIFT captures robust local keypoint descriptors. These complementary features are fused using a gated mechanism, enabling the model to adaptively weigh deep and handcrafted features for improved classification accuracy across varying crop patterns and imaging conditions.**

For crop area mapping, the Mobile Segment Anything Model (MobileSAM) is utilized to segment crop fields from georeferenced images. MobileSAM efficiently generates precise field boundaries, making it suitable for large-scale and resource-constrained deployments. The segmented crop regions are then used to compute the cultivated area by leveraging geospatial metadata, allowing accurate estimation of field size at specific locations. Experimental results demonstrate that the proposed approach effectively identifies crop types and reliably maps crop area, highlighting its potential for scalable, location-aware agricultural monitoring and decision support systems.

***Index Terms*—Geolocation-based area mapping, crop identification, crop area mapping, ResNet, SIFT, gated fusion model, MobileSAM, image segmentation, satellite imagery, Convolutional Neural Network**

I. Introduction

Agriculture plays a crucial role in food security and economic stability, especially in regions where large-scale monitoring of crop patterns is required for effective planning and decision-making. Traditional methods of crop identification and cultivated area estimation rely heavily on manual field surveys and farmer-reported data. These approaches are time-consuming, labor-intensive, and often prone to inaccuracies, particularly when applied over large geographic regions. With the increasing availability of high-resolution satellite and aerial imagery, there is a growing need for automated, geolocation-based systems that can accurately identify crop types and map cultivated areas in a scalable and reliable manner.

The primary problem addressed in this project is the lack of an integrated and efficient framework that simultaneously performs accurate crop type classification and precise crop area mapping using geospatial imagery. Variations in crop appearance due to seasonal changes, illumination conditions, and differences in growth stages make crop identification a challenging task. Additionally, accurately delineating crop field boundaries is essential for reliable area estimation, but conventional segmentation techniques often struggle with irregular field shapes and heterogeneous backgrounds.

To address these challenges, this project proposes a two-stage methodology that combines feature-level fusion for crop classification with advanced segmentation for area mapping. For crop identification, a gated fusion model is developed by integrating deep features extracted using a ResNet architecture with local handcrafted features obtained through the Scale-Invariant Feature Transform (SIFT). ResNet captures high-level semantic information from imagery, while SIFT provides robustness to scale, rotation, and illumination variations. The gated fusion mechanism adaptively combines these complementary features, enabling the model to emphasize the most informative representations for accurate crop prediction.

For crop area mapping, the Mobile Segment Anything Model (MobileSAM) is employed to segment crop fields from georeferenced images. MobileSAM efficiently generates precise segmentation masks for crop regions, making it suitable for large-scale and computationally constrained environments. The segmented field boundaries are then used in conjunction with geolocation metadata to calculate the cultivated area of each identified crop. By integrating classification and segmentation within a geolocation-aware framework, the proposed system provides an effective solution for automated crop monitoring, supporting applications in precision agriculture, resource management, and policy planning.

II. Literature Review

Accurate crop identification and crop area mapping play a vital role in modern agriculture by enabling data-driven decision-making. These techniques help farmers estimate crop yield, optimize resource usage such as water and fertilizers, and reduce operational risks. For governments, reliable crop and area statistics support yield forecasting, food security planning, subsidy allocation, and policy formulation. Auto-

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mated geospatial approaches significantly improve accuracy and scalability compared to traditional manual surveys.

Several studies have explored machine learning and deep learning techniques for crop classification using remote sensing data. Kamilaris and Prenafeta-Boldú [1] provided a comprehensive review of deep learning applications in agriculture, highlighting the effectiveness of convolutional neural networks (CNNs) for crop recognition from satellite imagery. Their work demonstrated that deep architectures outperform traditional classifiers in complex agricultural scenes.

To improve robustness, researchers have combined deep and handcrafted features. Li et al. [2] proposed a hybrid framework that integrates CNN features with local descriptors such as SIFT for crop classification, showing improved performance under varying illumination and scale conditions. This supports the motivation for using a gated fusion approach in crop identification tasks.

Field boundary detection and crop area estimation have also received significant attention. Waldner et al. [3] utilized satellite image segmentation techniques to delineate agricultural fields and estimate cultivated area, emphasizing the importance of accurate boundary extraction for yield assessment. Their study highlighted limitations of conventional segmentation methods when dealing with irregular field shapes.

Recent advancements in foundation models have further improved segmentation accuracy. Kirillov et al. [4] introduced the Segment Anything Model (SAM), which demonstrated strong generalization across diverse image domains, including remote sensing. Building on this, MobileSAM was proposed to enable efficient segmentation in resource-constrained environments, making it suitable for large-scale agricultural applications.

Additionally, geolocation-based crop monitoring systems have been explored for integrated analysis. Zhao et al. [5] developed a geospatial crop monitoring framework that combines crop classification with area estimation to support governmental decision-making and yield prediction. Their results confirm that integrating classification and segmentation within a geolocation-aware pipeline enhances agricultural monitoring accuracy.

III. Proposed Meathodoly

The proposed system begins with a user-provided input image of a crop field. This image is first processed by a hybrid crop classification model that combines ResNet-18 and SIFT features using a gated fusion mechanism. ResNet-18 extracts high-level deep visual features, while SIFT captures robust local descriptors. Simultaneously, geolocation information is extracted from the image metadata, and the obtained latitude–longitude coordinates are visualized using the Leaflet mapping. For crop area mapping, the satellite image is passed to the Mobile Segment Anything Model (MobileSAM), which segments the crop field from the background. The area is then calculated by counting the number of pixels belonging to the segmented crop region.This integrated pipeline provides both crop identification and precise area estimation in a geolocation-aware manner.

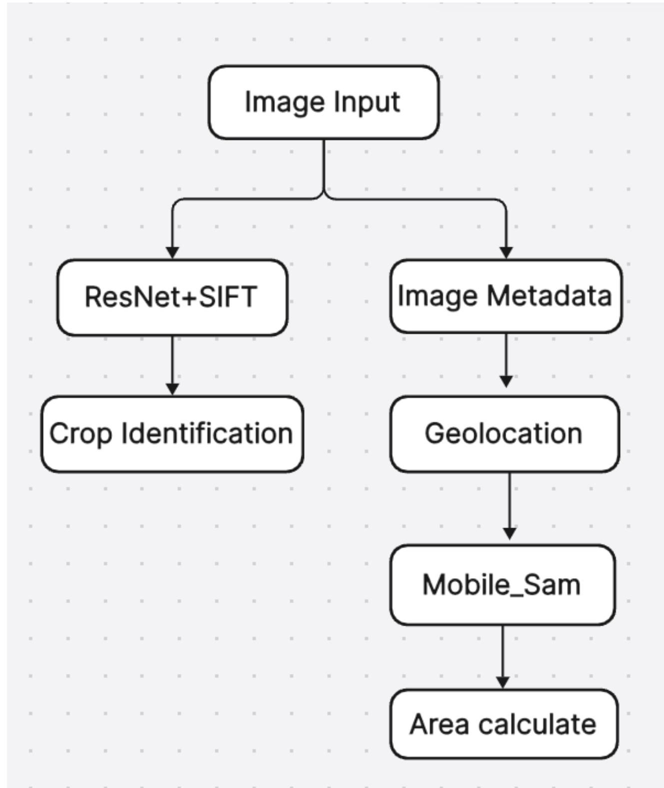


Fig. 1: Proposed Methodology for Crop Identification and Area Mapping

A. System Overview

In the crop identification module, the input image is processed through a sequence of feature extraction stages. First, the Scale-Invariant Feature Transform (SIFT) is applied to the image to extract robust local keypoint descriptors, resulting in a handcrafted feature vector that is invariant to scale, rotation, and illumination changes. In parallel, the same image is passed through a ResNet-18 deep convolutional neural network, which extracts high-level semantic features and produces a deep feature vector. These two feature vectors are then concatenated to form a unified representation of the image. The concatenated feature vector is fed into a final fully connected neural network, which performs classification and predicts the crop type present in the input image.

For crop area calculation, geolocation information is extracted from the image metadata, providing latitude and longitude coordinates corresponding to the crop field. These coordinates are utilized to locate and visualize the field using the Leaflet mapping framework. The input image is then processed using the Mobile Segment Anything Model (MobileSAM) to accurately segment the crop field. Then pixels in the field are calculated and using these pixel counts we calculate the are.

B. Dataset Description

The dataset used in this project consists of satellite and field-level images covering multiple major crops. For crop

TABLE I: Comparative Analysis of Related Research Works

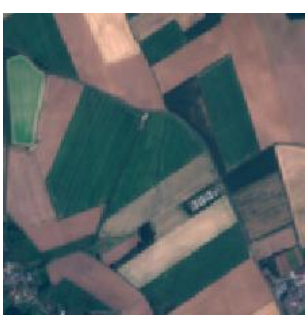
Paper	Technique Used	Accuracy	Dataset / Source
Kamilaris and Prenafeta-Boldú (2018) [1]	Comprehensive survey of CNN-based deep learning approaches for crop identification and agricultural analysis	– (Survey paper)	Multiple agricultural and remote sensing datasets
Li et al. (2020) [2]	Hybrid crop classification using CNN deep features fused with SIFT handcrafted features	∼90%	Sentinel-2 satellite imagery
Waldner et al. (2015) [3]	Satellite image segmentation and automated field boundary extraction for crop area estimation	∼85%	Landsat and SPOT satellite datasets
Kirillov et al. (2023) [4]	Segment Anything Model (SAM) for general-purpose image segmentation across domains	High qualitative accuracy	Large-scale mixed and open-domain image datasets
Zhao et al. (2021) [5]	Geolocation-based crop monitoring using CNN classification integrated with cultivated area estimation	∼88%	MODIS and Sentinel satellite imagery

identification, the dataset includes images belonging to nine crop classes: corn, mustard, black gram, groundnut, wheat, chickpea, soybean, pigeon pea, and millets. These images capture variations in crop appearance due to differences in growth stages, texture, and field conditions.

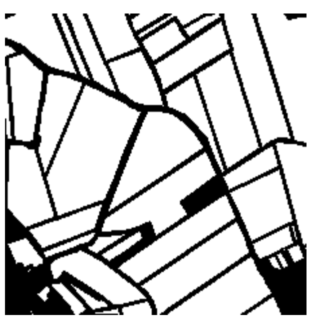
For crop area mapping, the dataset contains paired RGB satellite images and their corresponding binary mask images. The RGB images represent the original satellite view of agricultural fields, while the mask images highlight the exact boundaries of crop fields.

(a) Field image of Chickpea

(b) Field image of Blackgram



(c) Satellite RGB image



(d) Masked image of field

Fig. 2: Sample Dataset Images

C. Crop Identification

For crop identification we have employed gated fusion model where sift captures local robust points in the image and resnet-18 capture high level sematic features.

- The input crop image is first preprocessed and resized to a fixed resolution of 224×224 pixels to ensure compatibility with the ResNet-18 architecture.
- Scale-Invariant Feature Transform (SIFT) is then applied to the resized image to extract robust local keypoint descriptors, which are aggregated to form a handcrafted feature vector.
- In parallel, the same image is passed through the ResNet-18 convolutional neural network to extract high-level deep semantic features, resulting in a deep feature vector.
- The SIFT feature vector and the ResNet-18 feature vector are concatenated to create a unified representation that captures both local and global image characteristics.
- The concatenated feature vector is fed into a final neural network classifier, which predicts the crop type present in the input image.

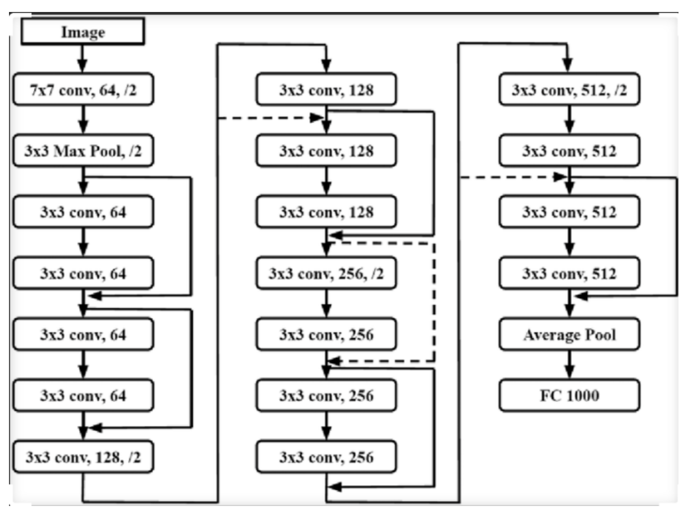


Fig. 3: ResNet-18 Architecture

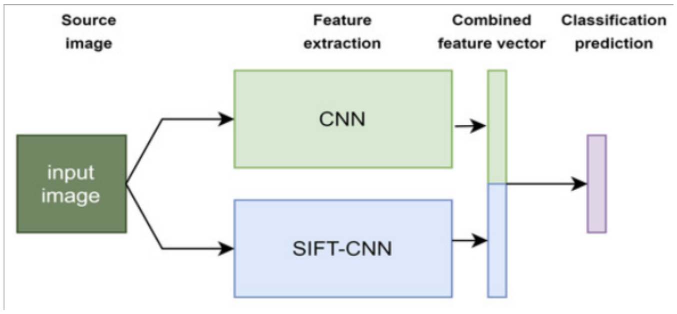


Fig. 4: Framework used for Crop Identification

D. Area Mapping

Mobile Segment Anything Model (MobileSAM) is trained using a labeled dataset consisting of RGB satellite images and their corresponding ground-truth mask images, where the mask represents the exact crop field region. During training, MobileSAM learns to distinguish crop fields from surrounding non-crop areas by leveraging spatial and contextual information present in the imagery.

During inference, the trained MobileSAM model is applied to the input satellite image to generate a segmentation mask of the crop field. The predicted mask highlights the crop field region at pixel level. The cultivated area is then computed by counting the number of pixels belonging to the segmented crop field.

The cultivated area of the crop field is calculated using the following relation:

$$\text{Area} = N_{\text{pixels}} \times (\text{GSD})^2 \tag{1}$$

- N_{pixels} total number of pixels belonging to the segmented crop field.
- GSD (Ground Sample Distance) is the ground distance represented by one pixel in the satellite image (meters per pixel).

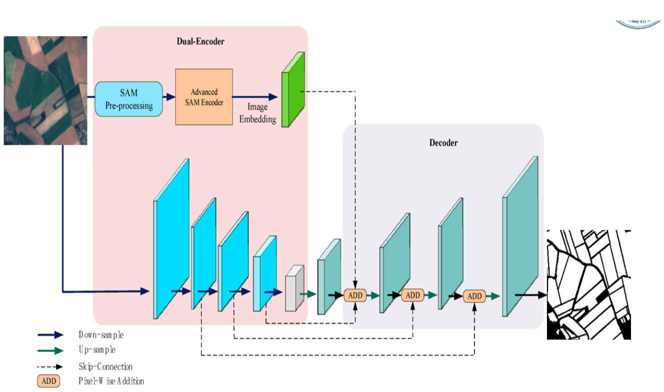


Fig. 5: Arcitecture of Mobile Sam

IV. Experiment Result and Discussion

A. Custom CNN

A custom convolutional neural network was initially implemented to establish a baseline for crop classification. However, the model exhibited underfitting behavior, as it was unable to learn discriminative features effectively from the dataset. Both training and testing accuracies remained low.

B. VGG16

The VGG16 architecture was evaluated to improve feature learning using a deeper pretrained network. Although VGG16 showed better performance compared to the custom CNN, the model failed to achieve significant improvement beyond an accuracy of approximately 60%. This limitation suggests that VGG16 was not able to generalize well to the given crop dataset.

C. ResNet-18

ResNet-18 demonstrated a noticeable improvement in classification performance by effectively learning deep hierarchical features. The model achieved high training accuracy; however, it suffered from overfitting, as the testing accuracy did not improve proportionally.While ResNet-18 captured detailed representations of the training data, it struggled to generalize well to unseen samples.

D. ResNet-18 + SIFT

The proposed ResNet-18 + SIFT gated fusion model achieved the best performance among all evaluated approaches. By combining deep features from ResNet-18 with robust handcrafted features from SIFT, the model effectively balanced learning and generalization. The proposed approach achieved a training accuracy of 81% and a testing accuracy of 79%, demonstrating consistent performance across both datasets and validating the effectiveness of feature-level fusion for crop identification.

E. Results

The SIFT + ResNet-18 pipeline achieved significantly better performance compared to earlier approaches.The model demonstrated high accuracy during testing. The SIFT capturesd local robust features which directly contributed to better classification performance, confirming the advantage of gated fusion model.

TABLE II: Classification Report for Crop Identification

Crop Class	Precision	Recall	F1-Score	Support
Black gram	0.87	0.76	0.81	17
Chickpea	0.92	0.96	0.94	47
Corn	0.87	0.94	0.90	49
Groundnut	0.87	0.81	0.84	16
Millets	0.98	0.93	0.95	44
Mustard	0.89	1.00	0.94	25
Pigeon pea	1.00	0.77	0.87	26
Soyabean	0.84	0.91	0.88	35
Wheat	0.94	0.92	0.93	36

F. Evaluation Metrics

To evaluate the performance of the proposed samples of fusion gated model, the commonly used classification metrics Precision, Recall, and F1-Score were employed. These metrics are mathematically expressed as follows:

TABLE III: Overall Performance Metrics

Metric	Value
Accuracy	0.9085
Macro Precision	0.9082
Macro Recall	0.8895
Macro F1-score	0.8959
Weighted Precision	0.9118
Weighted Recall	0.9085
Weighted F1-score	0.9078

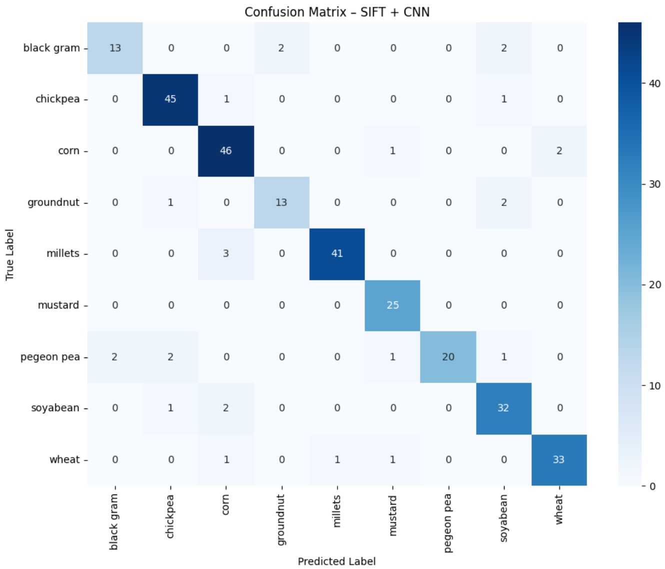


Fig. 6: Confusion Matrix

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3}$$

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

In the above equations:

- **True Positives (TP):** Number of samples correctly classified as belonging to the target class.
- **False Positives (FP):** Number of samples incorrectly predicted as belonging to the target class, even though they are not.
- **False Negatives (FN):** Number of samples that belong to the target class but were not detected by the model.
- **True Negatives (TN):** Number of samples correctly identified as not belonging to the target class.

Precision reflects how many of the predicted positives are actually correct, while Recall measures the model's ability to detect all actual positive samples. The F1-Score provides a balanced evaluation by combining both Precision and Recall.

The confusion matrix summarizes classification model performance, with rows representing actual class instances and columns representing predicted class instances. The matrix visualization demonstrates classification performance across 9 classes.

V. Conclusion

This project presented a geolocation-based framework for crop identification and crop area mapping using satellite and field-level imagery. A hybrid crop classification approach was developed by integrating ResNet-18 deep features with SIFT handcrafted features through feature-level fusion, enabling robust crop recognition across varying field conditions. Experimental results demonstrated that traditional CNN models and standalone deep networks either underperformed or suffered from underfitting and overfitting, whereas the proposed ResNet-18 + SIFT model achieved consistent performance with training and testing accuracies of 81% and 79%, respectively.

For crop area mapping, MobileSAM was trained on labeled RGB and mask satellite images to accurately segment crop field boundaries. The cultivated area was estimated by counting the number of pixels within the segmented crop region and converting them into real-world area using ground sample distance. The integration of crop classification, geolocation extraction, and efficient segmentation provides a scalable and reliable solution for automated agricultural monitoring. Overall, the proposed system demonstrates strong potential for supporting precision agriculture, yield estimation, and data-driven decision-making for farmers and government agencies.

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