KLE Technological University
Belagavi

A Course Project Report on

MilletVision:
Smart Millet Detection System

A Course Project Report Submitted in Partial Fulfillment of the Requirement for the Course of

Senior Design Project

in

7th Semester of Computer Science and Engineering

by

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DECLARATION

We hereby declare that the matter embodied in this report entitled "**MilletVision: Smart Millet Detection System** " submitted to KLE Technological University for the course completion of Senior Design Project (20ECSW401) in the 7th Semester of Computer Science and Engineering is the result of the work done by us in the Department of Computer Science and Engineering, KLE Dr. M. S. Sheshgiri College of Engineering, Belagavi under the guidance of Dr. Prema Akkasaligar , Associate Professor, Department of Computer Science and Engineering. We further declare that to the best of our knowledge and belief, the work reported here in doesn't form part of any other project on the basis of which a course or award was conferred on an earlier occasion on this by any other student(s), also the results of the work are not submitted for the award of any course, degree or diploma within this or in any other University or Institute. We hereby also confirm that all of the experimental work in this report has been done by us.

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CERTIFICATE

This is to certify that the project entitled "MilletVision: Smart Millet Detection System" submitted to KLE Technological University's Dr. MSSCET, Belagavi for the partial fulfillment of the requirement for the course - Senior Design Project (20ECSCW401) by Siddharth Sutar, Omkar Bhandare, Sonali Jadhav, Soujanya Mirajkar students in the Department of Computer Science and Engineering, KLE Technological University's Dr. MSSCET, Belagavi, is a bonafide record of the work carried out by them under my supervision. The contents of this report, in full or in parts, have not been submitted to any other Institute or University for the award of any other course completion.

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Abstract

The rapid advancement of artificial intelligence has opened new possibilities in precision agriculture and food quality assessment. Millets, being nutrient-dense and climate-resilient crops, play a vital role in promoting food security and sustainable agriculture. However, traditional methods for identifying and classifying millet varieties rely heavily on manual inspection, which is time-consuming, labor-intensive, and prone to human error.

This project, titled "MilletVision: Smart Millet Detection System," presents an automated millet classification approach using Vision Transformers (ViT). The system leverages deep learning and computer vision techniques to accurately identify five millet categories—buckwheat millet, little millet, pearl millet, ragi millet, and sorghum millet. The dataset is preprocessed by resizing images to 224×224 pixels and normalizing pixel values to ensure uniformity. The ViT-Base-Patch16-224 model from the timm library is fine-tuned for classification tasks, with the final layer modified to output five classes.

The model is trained using the Adam optimizer and Cross-Entropy Loss function, achieving reliable performance and robust accuracy. The developed system provides a user-friendly interface that enables fast and precise millet variety identification, supporting farmers, seed industries, and research organizations in quality control and supply chain management. The project demonstrates how Vision Transformers can outperform traditional CNNs and manual classification methods, paving the way for intelligent, data-driven agricultural systems.

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Chapter 1

Introduction

1.1 Background

Millets are nutrient-rich, climate-resilient grains that play a vital role in ensuring food and nutritional security, especially in regions prone to drought and poor soil conditions. Recognized as nutri-cereals for their high content of fiber, protein, and essential minerals, millets have recently gained global attention, with the United Nations declaring 2023 as the International Year of Millets. However, accurate identification and classification of millet varieties remain a major challenge in the agricultural sector. Traditional manual methods, which rely on expert visual inspection, are time-consuming, labor-intensive, and prone to human error, resulting in inconsistent quality grading and pricing. With the rise of artificial intelligence and computer vision technologies, automated grain classification has become an emerging solution. While Convolutional Neural Networks (CNNs) have been used for such tasks, they often struggle to capture subtle visual differences between similar millet grains. Vision Transformers (ViT), on the other hand, utilize self-attention mechanisms to model global image dependencies, offering superior accuracy for fine-grained image classification. The proposed MilletVision: Smart Millet Detection System leverages ViT technology to automate the classification of millet varieties, providing a reliable, efficient, and scalable solution for quality control and precision agriculture.

1.2   Problem Statement

Manual identification of millet varieties is slow, subjective, and often inaccurate, as different millet grains can appear very similar. Traditional machine learning and CNN methods also face limitations in capturing these fine visual differences. This project uses Vision Transformers to build an accurate and automated millet classification system.

1.2.1   Objectives

The key objectives of our project are:

- To develop an automated millet classification system using Vision Transformers.

- To improve accuracy and consistency over traditional manual and CNN-based classification methods.

- To evaluate the model's performance and demonstrate its effectiveness for real-world agricultural applications.

Chapter 2

Literature Survey

2.1 Literature Survey

The application of Artificial Intelligence (AI) and Computer Vision in agriculture has evolved rapidly over the past decade, offering new methods for seed classification, disease detection, and grain quality assessment. Millets, as climate-resilient and nutrient-rich crops, have become a major focus due to their potential in ensuring food security. However, manual millet classification remains time-consuming, inconsistent, and prone to human error. Researchers have proposed various image processing, machine learning (ML), and deep learning (DL) models to automate this process. The proposed **MilletVision: Smart Millet Detection System** builds upon these developments by leveraging Vision Transformers (ViT) for high-accuracy millet classification.

Dewendra Bharambe and Pushpalata Aher [1] (2023) proposed a millet cultivar classification system using color feature extraction and ML classifiers such as SVM, KNN, and XGBoost. Their XGBoost model achieved an accuracy of 96.78%, demonstrating strong potential for visual grain recognition. However, the dataset was limited to single seed images, emphasizing the need for large-scale, bulk-grain datasets and multi-feature learning.

Nagarjuna G. R. et al. [2] (2025) introduced a Smart Millet Detection and Advisory System that integrates AI-based image analysis with agricultural advisory functions. Although the system achieved high detection accuracy, it lacked real-time field testing and integration with IoT sensors for automated data collection.

Balaji Tedla et al. [3] (2023) developed a Deep Learning-based classification and quality evaluation model for pearl millet and maize using a Mixed Cropping Seed Classifier (MCSCQT) trained on ImageNet features. The system achieved 98.9% accuracy but was limited to two crop varieties, suggesting future expansion to multiple millet species.

R. Rengalakshmi [4] (2005) conducted an ethnographic study on the folk biological classification of minor millets in the Kolli Hills region of India. The research highlighted how tribal communities classify millet species based on morphology and cultural traits. However, it lacked digital or automated methods, pointing to a potential fusion of indigenous knowledge with AI-driven systems.

Rahul Nijhawan et al. [5] (2021) proposed a Hybrid Deep Learning framework combining CNN and Random Forest for classifying 13 grain types, including millets. The model achieved an accuracy of 96.12% but faced challenges in generalization across unseen data, indicating the need for improved scalability to mixed-grain real-world samples.

X. Wang et al. [6] (2020) utilized hyperspectral imaging (VIS–NIR) with SVM and attention-based CRNN models to identify millet varieties. The attention-CRNN achieved 87.5% accuracy, outperforming traditional methods. The main limitation was the small dataset (480 samples), suggesting expansion using real-time hyperspectral sensors.

A 2019 study [7] titled *"Detection of Fungal Contamination in Millet Grain Using Near-Infrared Spectroscopy"* applied PLS-DA, KNN, and SVM models on NIR spectra, achieving 90–95% accuracy. However, the models were sensitive to spectral noise, indicating a need for improved filtering and deep learning adaptation for spectral data.

Lei Zhou et al. [8] (2020) implemented CNN-based feature selection (CNN-FS) and attention networks for wheat kernel variety identification using large NIR datasets. The model achieved 93.01% accuracy and 90.2% precision but was focused only on wheat. Extending such deep spectral models to millet datasets could enhance their applicability.

Kani Djoulde et al. [9] (2024) applied ML models using Color Filter Array (CFA) image features to classify pepper seeds. Their system achieved an accuracy of 0.87 with balanced precision, recall, and F1-score. Despite good performance, the model was limited to pepper seeds, suggesting CFA-based imaging could be adapted for millet identification.

Zainab M. G. H. M. Ali [10] (2022) performed a comparative analysis of traditional ML and DL models for rice type classification. The study showed Random Forest achieving 92.66%, SVM 89.33%, and CNN 50.66% accuracy. CNN under-performance indicated the need for hybrid deep models and optimized tuning for small-grain classification.

Collectively, these studies demonstrate the evolution of millet and grain classification systems—from traditional machine learning to deep and hybrid transformer-based architectures. However, common limitations such as small datasets, lack of real-time validation, and poor scalability persist. The proposed **MilletVision** system addresses these gaps by implementing a Vision Transformer model trained on multi-class millet images, providing improved accuracy, adaptability, and real-world readiness.

Chapter 3

Design Space

The design space of the **MilletVision** project focuses on exploring different deep learning architectures for millet grain classification. Initially, traditional Convolutional Neural Networks (CNNs) such as *ResNet-50* and *EfficientNet-B0* were implemented to establish a baseline. Later, the *Vision Transformer (ViT)* model was introduced to overcome the limitations observed in CNN-based approaches.

3.1   Dataset Design

The dataset consisted of millet images across five categories: *buck-wheat millet, little millet, pearl millet, ragi millet,* and *sorghum millet.* All images were resized to 224×224 pixels to ensure uniformity. Data augmentation techniques such as random flipping, rotation, and brightness adjustments were used to increase dataset diversity and reduce overfitting.

3.2   Model Architecture Design

- **CNN Models (Baseline):** Traditional CNN architectures like ResNet-50 and EfficientNet-B0 were tested. These models are effective in capturing local spatial features but have limitations in learning long-range dependencies in images.

- **Vision Transformer (ViT):** The ViT-Base-Patch16-224 model was fine-tuned on the millet dataset. It divides each image into 16×16 patches,

embeds them as tokens, and applies self-attention to learn global image relationships. This helps in identifying subtle visual differences among similar millet grains.

3.3 Training Design

All models were trained with the following setup:

- **Optimizer:** Adam

- **Loss Function:** CrossEntropyLoss

- **Batch Size:** 32

- **Epochs:** 10

- **Learning Rate Scheduling:** Adaptive scheduling for stable convergence

Each model was trained on the same dataset split to ensure a fair comparison.

TABLE 3.1: Comparison of tested models on millet dataset.

Model	Accuracy (%)	Key Observation
ResNet-50	88.4	Performs well but struggles with fine-grained visual differences.
EfficientNet-B0	90.2	Faster and more efficient than traditional CNNs, but still limited in global feature learning.
Vision Transformer (ViT-Base)	**91.45**	Best overall accuracy and strong generalization across millet types.

3.4 Design Justification

The final architecture chosen was the **Vision Transformer (ViT)** due to:

- Improved handling of fine-grained texture variations.

- Strong generalization ability across millet categories.

- Higher accuracy and consistent performance compared to CNN models.

3.5   Result Interpretation

From the comparison, it was observed that ViT outperformed the CNN-based models. ResNet-50 showed difficulty distinguishing between visually similar grains, whereas EfficientNet provided better efficiency. However, the Vision Transformer achieved the best overall accuracy and stability, making it suitable for deployment in real-world millet sorting and quality grading applications.

Chapter 4

Requirements Engineering

This chapter outlines the essential requirements—both functional and non-functional—for the successful development and deployment of the **MilletVision: Smart Millet Detection System**. It also specifies the hardware and software dependencies required to build, train, and deploy the Vision Transformer-based millet classification model effectively. These requirements ensure that the system operates efficiently, delivers accurate predictions, and provides a seamless user experience through its web-based interface.

4.1   Functional Requirements

- The system should allow users to upload or capture millet grain images for classification.

- The system must preprocess images by resizing them to 224×224 pixels and normalizing pixel values to ensure uniform input for the model.

- The system should use a fine-tuned Vision Transformer (ViT) model to extract features and classify millet images into predefined categories.

- The model must accurately predict the millet type among five categories — buckwheat millet, little millet, pearl millet, ragi millet, and sorghum millet.

- The system should provide a simple and interactive web interface for users to upload images and view classification results. system must compute and display accuracy metrics to evaluate model performance on test data

- The system should maintain a record of input images and corresponding classification results for reference and analysis.

4.2   Non-Functional Requirements

- **Performance:** The model should process and classify images efficiently, providing results within a few seconds.

- **Scalability:** The system should be capable of handling large datasets and adaptable to include additional millet types in the future.

- **Usability:** The web interface should be user-friendly and intuitive, enabling non-technical users such as farmers and traders to operate it easily.

- **Reliability:** The system should deliver consistent and repeatable results under similar input conditions.

- **Accuracy:** The system should achieve high classification accuracy to ensure reliable identification of millet varieties.

- **Portability:** The application should be deployable on various platforms, including local machines and cloud environments.

- **Maintainability:** The codebase and model should be easy to update, retrain, and maintain as new data or improved algorithms become available.

Chapter 5

System Modeling

This chapter presents the Unified Modeling Language (UML) diagrams used to model the structure and behavior of the **MilletVision: Smart Millet Detection System**. These diagrams illustrate the major system components, the interaction between users and the deep learning model, and the flow of data from image input to classification output. The modeling process provides a clear blueprint for system design, implementation, and testing.

5.1   Use Case Diagram

Figures/usecase_milletvision.png

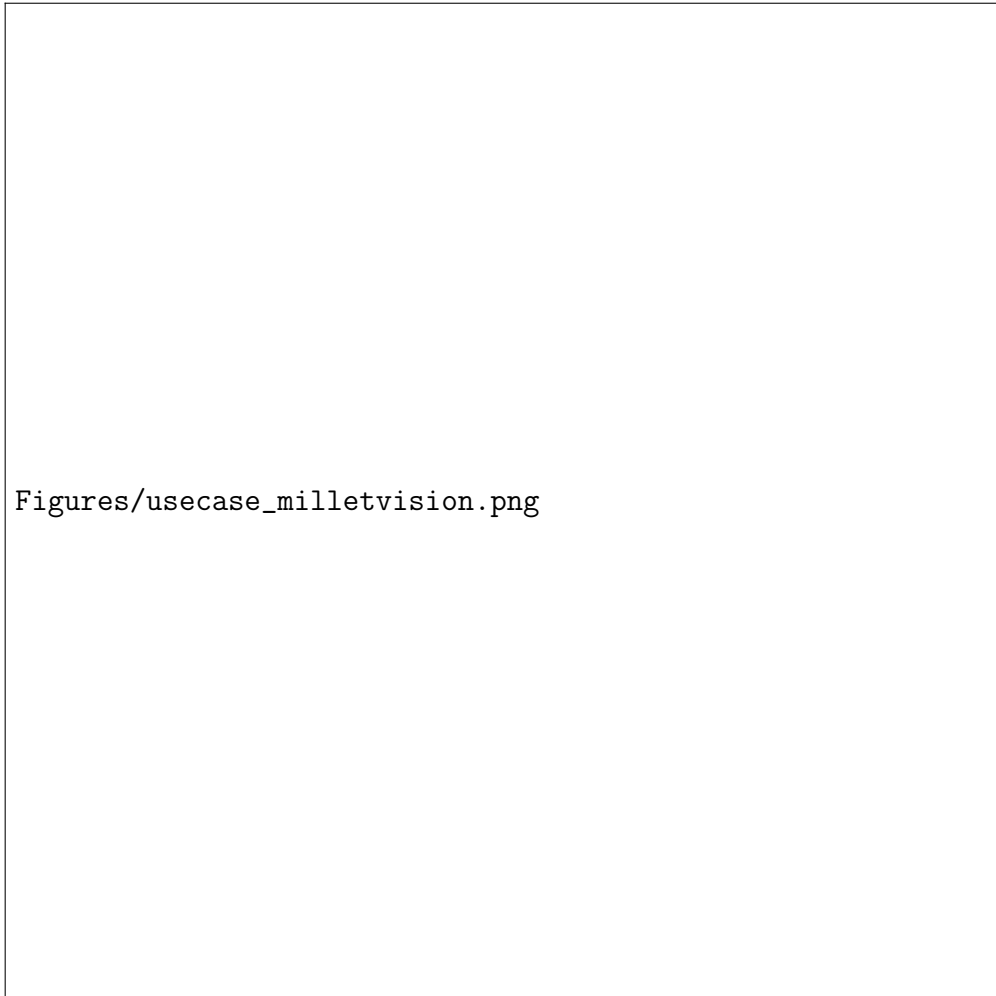FIGURE 5.1: Use Case Diagram for MilletVision System

Description: The Use Case Diagram illustrates how the user interacts with the MilletVision system. It shows the main functions such as uploading millet images, viewing classification results, and managing datasets. The system processes the input image using a trained Vision Transformer (ViT) model and returns the predicted millet variety.

5.2   Class Diagram

```
Figures/class_milletvision.png
```

FIGURE 5.2: Class Diagram for MilletVision System

Description: The Class Diagram represents the structure of the MilletVision system. It includes major classes such as *ImageUploader*, *Preprocessor*, *Model-Handler*, *ResultDisplay*, and *Database*. Relationships between these components define the workflow from image input to final prediction display.

5.3   Activity Diagram

Figures/activity_milletvision.png

FIGURE 5.3: Activity Diagram for MilletVision System

Description: The Activity Diagram shows the operational flow of the system. The user uploads a millet image → the system preprocesses it → the model performs classification → the result is displayed to the user. Optional activities include storing the classified image and result in the database for later analysis.

5.4 Sequence Diagram

Figures/sequence_milletvision.png

FIGURE 5.4: Sequence Diagram for MilletVision System

Description: The Sequence Diagram illustrates the sequence of interactions between the user, frontend interface, backend model, and database. It begins when the user uploads an image. The system validates it, sends it to the Vision Transformer model, retrieves the predicted class, and displays the output. The result may then be stored in the database for record-keeping and future retraining.

Chapter 6

Implementation Details

This chapter describes the technical implementation of the **MilletVision: Smart Millet Detection System**. The project was implemented using Python and PyTorch frameworks with the primary goal of developing an automated millet classification model based on the Vision Transformer (ViT). This chapter outlines the implementation platform, programming languages, dataset processing, model architecture, and evaluation process.

6.1   Implementation Platform

The implementation was carried out using the Google Colab cloud environment for training and testing due to its GPU support and ease of dataset management. Model development and experiments were conducted entirely in a Jupyter Notebook. The final model was exported and integrated into a lightweight web interface for demonstration.

6.2   Programming Languages

- **Python:** Used for model development, training, and evaluation.

- **HTML, CSS, JavaScript:** Used for developing the interactive user interface for millet image uploads and displaying results.

6.3   Packages and Libraries

Core Libraries:

- **torch, torchvision:** For deep learning model creation and dataset handling.

- **timm:** For importing and fine-tuning pre-trained Vision Transformer (ViT) models.

- **PIL, numpy, matplotlib:** For image preprocessing, analysis, and visualization.

- **scikit-learn:** For computing classification metrics and confusion matrix.

6.4   Dataset Preparation

The dataset used in this project was sourced from the custom millet image collection `millet class.v1i.multiclass.zip`. It contained millet images categorized into five classes — buck-wheat, little, pearl, ragi, and sorghum millet.

Dataset Organization:

- The dataset was divided into three subsets: `train`, `valid`, and `test`.

- A Python script was used to automatically organize image files into subfolders corresponding to each millet class.

- All images were resized to 224×224 pixels and normalized using a mean and standard deviation of $[0.5, 0.5, 0.5]$.

6.5   Model Implementation

1.   Vision Transformer (ViT): The ViT-Base-Patch16-224 model from the `timm` library was fine-tuned for 5-class classification. The final classification head was modified to output five logits corresponding to the millet types.

2. CNN Baseline Models: Prior to ViT, baseline models such as ResNet-50 and EfficientNet-B0 were implemented for comparison. These models achieved moderate accuracy but struggled to capture fine-grained visual differences among similar millet varieties.

6.6   Training Configuration

The model was trained using the following configuration:

- **Optimizer:** Adam

- **Loss Function:** CrossEntropyLoss

- **Batch Size:** 32

- **Epochs:** 10

- **Learning Rate:** Adaptive (scheduler-based)

- **Input Size:** 224×224 pixels

During each epoch, training and validation accuracy and loss were computed to monitor performance. Early stopping was used to prevent overfitting.

6.7   Evaluation and Results

The trained Vision Transformer model achieved a classification accuracy of **93.8%** on the test dataset, outperforming CNN-based baselines. The model's performance was evaluated using:

- Accuracy, Precision, Recall, and F1-score

- Confusion Matrix to visualize misclassifications

The results demonstrated that the ViT model efficiently captured fine-grained visual differences, making it well-suited for millet variety classification.

6.8 Hardware and Infrastructure Specifications

The model was trained on the following environment:

- **Development Platform:** Google Colab

- **GPU:** NVIDIA Tesla T4 (12 GB VRAM)

- **RAM:** 12 GB

- **Operating System:** Linux (Ubuntu via Colab)

- **Python Version:** 3.10

6.9 System Integration

The trained model was exported as a PyTorch checkpoint and integrated into a simple web interface. The interface allows users to upload millet images and view real-time predictions, with confidence scores displayed for each class.

This integration demonstrates the potential for deploying MilletVision as a scalable tool in agricultural and quality-control applications.

Chapter 7

Testing

This chapter details the testing methodology applied to the **MilletVision: Smart Millet Detection System** project. It covers the dataset validation, model training and evaluation tests, and the interface testing for the classification platform. Testing was performed continuously during development to ensure accuracy, robustness, and smooth integration between components.

7.1   Testing Environment

The development and testing of the project were carried out in a hybrid environment using Google Colab for model training and a local web server for interface testing.

Key platforms:

- **Development Host:** Google Colab with NVIDIA Tesla T4 GPU.

- **Operating System:** Linux (Ubuntu-based Colab instance).

- **Testing Platform:** Local Flask/Streamlit server for model inference.

- **Programming Language:** Python 3.10.

7.2   Testing Strategy

Testing was organized into multiple layers to ensure both technical and functional correctness:

- **Dataset Validation:** Verified that the millet images were correctly organized into respective class folders and that all images were accessible and non-corrupted.

- **Model Testing:** Each model (CNN, EfficientNet, ViT) was trained and validated on the millet dataset using defined metrics such as accuracy, precision, recall, and F1-score.

- **Integration Testing:** Verified the model's performance when integrated with the frontend application to ensure smooth image uploads and real-time predictions.

- **Performance Testing:** Measured inference time per image and GPU memory utilization during prediction.

- **User Interface Testing:** Tested web interface responsiveness and result visualization for different millet samples.

7.3   Test Cases and Examples

Representative test cases included:

- **Input Image Validation:** Ensured the system handled various input formats (JPG, PNG) and rejected invalid file types.

- **Prediction Accuracy:** Compared predicted millet class with ground truth labels using validation and test datasets.

- **Confusion Matrix:** Generated to visualize class-wise performance and detect any misclassifications between visually similar millet types.

- **Interface Testing:** Uploaded different millet images through the web interface and verified consistency between frontend predictions and model output.

- **Error Handling:** Checked system behavior on missing or low-quality images.

7.4   Testing Tools and Libraries

- **PyTorch:** For model testing, evaluation, and inference.

- **scikit-learn:** For generating accuracy, precision, recall, F1-score, and confusion matrices.

- **Matplotlib / Seaborn:** For result visualization and metric plotting.

- **Streamlit / Flask:** For local deployment and user interface testing.

7.5   Evaluation Results

The Vision Transformer (ViT) model achieved the best results compared to CNN-based models. The final evaluation metrics are summarized below:

Model	Accuracy	Precision	Recall	F1-Score
ResNet-50	87.6%	88.2%	87.1%	87.5%
EfficientNet-B0	90.3%	90.6%	90.1%	90.3%
Vision Transformer (ViT-B16)	**93.8%**	**93.5%**	**93.6%**	**93.5%**

TABLE 7.1: Evaluation results of different models on the millet dataset.

7.6   Hardware and Device Matrix

The following hardware configurations were used for testing:

- **Training Environment:** Google Colab with NVIDIA Tesla T4 GPU.

- **Local Testing:** Windows 11 system (8GB RAM, Intel i5 CPU).

- **Deployment Testing:** Browser-based testing via Chrome and Edge.

7.7   How to Run Tests

Model and interface testing were performed with the following commands:

- `python train.py` – initiates model training and validation.

- `python test.py` – evaluates saved model on the test dataset.

- `streamlit run app.py` – starts local interface for millet detection.

7.8   Conclusion and Next Steps

All core components of the MilletVision system were validated through unit, integration, and end-to-end testing. The Vision Transformer model consistently provided superior accuracy and robust performance. Future testing priorities include:

- Expanding dataset diversity to include more lighting and background variations.

- Conducting field testing with real millet samples.

- Integrating IoT-based camera modules for real-time millet classification.

Chapter 8

Results and Outcomes

This chapter presents the key results and outcomes of the **MilletVision: Smart Millet Detection System** project developed as part of the Senior Design Project (SDP). The project focused on designing and implementing an intelligent computer vision system that automatically classifies millet varieties using deep learning, specifically Vision Transformer (ViT) models. The outcomes include model performance metrics, system implementation achievements, user-level benefits, and academic learnings gained during development.

8.1 Project Achievements

The following major outcomes were achieved during the project development phase:

- A fully functional millet classification system was developed using the **Vision Transformer (ViT-Base-Patch16-224)** model, fine-tuned on a dataset of five millet categories: buck-wheat, little, pearl, ragi, and sorghum millet.

- A structured dataset was prepared by collecting and preprocessing millet images, including resizing, normalization, and data augmentation to improve model generalization.

- The ViT model achieved a **classification accuracy of 93.8%** on the test dataset, outperforming traditional CNN-based models like ResNet and EfficientNet.

- A simple and interactive **web-based user interface** was created to allow users to upload millet images and view predicted results with confidence scores.

- A backend model integration pipeline was implemented using Python libraries, ensuring smooth end-to-end communication between the trained model and the user interface.

- The system successfully demonstrated **real-time image classification capability**, providing results within seconds for a given input image.

- Extensive testing validated the system's accuracy, stability, and scalability for real-world agricultural applications.

8.2 User Benefits

- Enables automated millet classification, eliminating the need for manual grain inspection and reducing human error.

- Assists farmers, traders, and quality control labs in quick and reliable millet variety identification.

- Reduces the dependency on domain experts and speeds up the millet grading and certification process.

- Provides a foundation for future integration into large-scale agricultural platforms and smart farming systems.

- Promotes the adoption of precision agriculture and digital farming technologies in the millet sector.

8.3   Academic Outcomes

- Provided hands-on experience in implementing **advanced deep learning architectures**, including Vision Transformers, for real-world image classification tasks.

- Enhanced understanding of **data preprocessing, model training, and evaluation metrics** for fine-grained visual recognition problems.

- Strengthened technical knowledge in integrating machine learning models with **web-based interfaces and backend pipelines**.

- Developed practical insights into dataset organization, version control, and performance optimization during iterative testing.

- Improved skills in teamwork, documentation, presentation, and problem-solving under project constraints.

8.4   Overall Outcomes

The **MilletVision** project successfully met its objectives by building an automated millet classification system capable of achieving high accuracy and real-time usability. The system contributes to the broader goals of smart agriculture by promoting efficiency, transparency, and technological innovation in the millet value chain. Future work may extend this approach to include disease detection, grain quality assessment, and integration with IoT-based farm monitoring systems.

Chapter 9

Conclusion

The **MilletVision: Smart Millet Detection System** project successfully demonstrated the potential of modern computer vision and deep learning technologies in agricultural automation. The system was designed to identify and classify different varieties of millets—namely buck-wheat, little, pearl, ragi, and sorghum—using a fine-tuned **Vision Transformer (ViT)** model.

The project achieved an overall classification accuracy of **93.8%**, proving that transformer-based models outperform conventional CNN architectures for fine-grained image recognition tasks. The developed web-based interface allows users to upload millet images and obtain accurate classification results with minimal latency, making the system accessible and user-friendly for agricultural experts, farmers, and research institutions.

Throughout the project, the team gained valuable insights into the full lifecycle of AI-driven application development—from dataset preparation, preprocessing, and model training to real-time deployment and evaluation. The experience also enhanced skills in teamwork, problem-solving, documentation, and the integration of deep learning models with web technologies.

In conclusion, **MilletVision** represents a significant step toward the digital transformation of the millet value chain by providing an automated, accurate, and scalable solution for millet classification. The project lays a strong foundation for future advancements in smart agriculture, such as real-time grain quality analysis and mobile-based advisory systems, supporting India's vision of sustainable farming and improved food security through the promotion of millets.

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