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Vasundhara: An AI-Driven Framework for Automated Verification and Gamification of Environmental Activities

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ABSTRACT: Promoting sustainable environmental behavior at scale requires reliable mechanisms to verify and incentivize citizen participation. However, existing platforms largely rely on manual auditing or trust-based self-reporting, which limits scalability and credibility. This paper presents Vasundhara, a confidence-aware AI-driven framework for automated verification and gamification of environmental activities.

The proposed system integrates a web-based platform with a deep learning-based image verification service to validate four categories of activities: cleanup, tree planting, recycling, and eco-friendly commuting. A convolutional neural network based on a pre-trained ResNet50 architecture is employed using transfer learning to classify user-submitted images. To ensure reliability in real-world deployment, we introduce a confidence-guided decision pipeline in which high-confidence predictions are automatically approved or rejected, while low-confidence cases are forwarded for human review.

The complete system is implemented using PHP and MySQL for platform management and a Python-based microservice for AI inference. A curated dataset of 1,200 images is used for training and evaluation. Experimental results demonstrate that the proposed system achieves an overall classification accuracy of 94.96% and significantly outperforms lightweight baseline models. The results indicate that confidence-aware AI-based verification combined with gamification can provide a scalable and trustworthy solution for promoting environmental sustainability.

KEYWORDS: Environmental Sustainability, Activity Verification, Machine Learning, ResNet50, Gamification, AI Systems, Confidence-Based Decision Making

I. INTRODUCTION

1.1 Background

Environmental degradation caused by pollution, deforestation, and improper waste management has emerged as one of the most critical challenges of the 21st century. Although governments and international organizations continue to introduce policies and large-scale environmental programs, the cumulative impact of individual and community-level actions—such as tree plantation, waste recycling, cleanup drives, and the adoption of eco-friendly transportation—remains a crucial yet underexploited factor in achieving sustainability goals.

With the rapid growth of digital platforms and mobile technologies, there is significant potential to use technology to improve the reach and effectiveness of environmental programs. Nevertheless, most existing digital systems still rely heavily on manual verification or trust-based reporting, which raises concerns regarding scalability, credibility, and misuse. These limitations highlight the need for an intelligent, automated, and scalable framework that can reliably verify user-contributed environmental activities while simultaneously providing transparent and motivating incentive mechanisms.

1.2 Problem Statement

Despite the growing number of environmental campaigns and digital sustainability initiatives, large-scale public participation remains difficult to sustain due to several fundamental challenges. One of the most critical issues is the lack of a scalable and reliable mechanism for verifying user-reported environmental activities. Manual verification of visual evidence, such as images from cleanup drives or plantation activities, is labor-intensive, time-consuming, and prone to human error, making it impractical for systems with a large number of participants.

Furthermore, there exists a significant information gap between users and reliable sources of guidance on sustainable practices. Participants often lack immediate access to trustworthy and context-aware information related to activities such as waste segregation, recycling methods, or environmentally responsible behavior. These combined limitations highlight the need for a unified system that can simultaneously address scalability, reliability, user motivation, and informational support within a single integrated framework.

1.3 Proposed Solution: Vasundhara

To address the above challenges, this paper proposes **Vasundhara**, an AI-driven web-based framework for automated verification and gamification of environmental activities. The system integrates a computer vision-based verification module with a reward-driven incentive mechanism to ensure both reliability and sustained user engagement.

Once an activity is verified, the user is awarded “Green Credits,” which form the basis of the gamification system. In addition, the platform integrates an AI-powered conversational assistant to provide guidance and improve user interaction. Thus, Vasundhara serves as a complete and practical framework for scalable and trustworthy verification of environmental activities.

1.4 Objectives

The specific objectives of this project are:

- To design and implement a web-based platform for logging and managing environmental activities such as cleanup, planting, cycling, and recycling.
- To develop a CNN-based image classification module using the ResNet50 architecture for automated verification of user-submitted activity images.
- To incorporate a gamified reward mechanism in which successfully verified activities are converted into virtual credits to encourage sustained participation.
- To integrate an AI-powered conversational assistant to improve user interaction and provide guidance related to environmental sustainability

II. LITERATURE REVIEW

Environmental sustainability initiatives often struggle to verify and measure individual contributions at scale. Traditional methods rely on manual auditing or self-reporting, leading to inconsistencies and poor scalability. Early machine learning approaches using handcrafted features were limited in handling real-world image variability, such as lighting changes, background noise, and quality differences. Recent advancements in deep learning, especially Convolutional Neural Networks (CNNs), have significantly improved image classification and visual recognition.

2.1 Evolution of Automated Image Verification

Earlier computer vision systems depended on handcrafted features like edge detection and color histograms, which worked only in controlled environments. Deep learning introduced models such as AlexNet and VGG, enabling automatic feature learning from data. ResNet architectures further improved performance by using residual connections, allowing deeper networks without degradation. Transfer learning, where models trained on datasets like ImageNet are adapted for specific tasks, has made image verification practical for applications such as environmental activity recognition.

2.2 Gamification in Sustainability Platforms

Gamification—using elements like points, badges, and leaderboards—has proven effective in increasing user engagement in areas like health and education. However, many environmental platforms rely on self-reported actions, reducing reliability. Integrating automated image verification with gamification

2.3 Role of Large Language Models (LLMs)

Advances in Large Language Models (LLMs) have enabled more natural and interactive user experiences compared to rule-based chatbots. These systems can provide guidance, feedback, and relevant information effectively. LLMs can also summarize user progress and offer personalized suggestions, enhancing usability.

III. PROPOSED METHODOLOGY

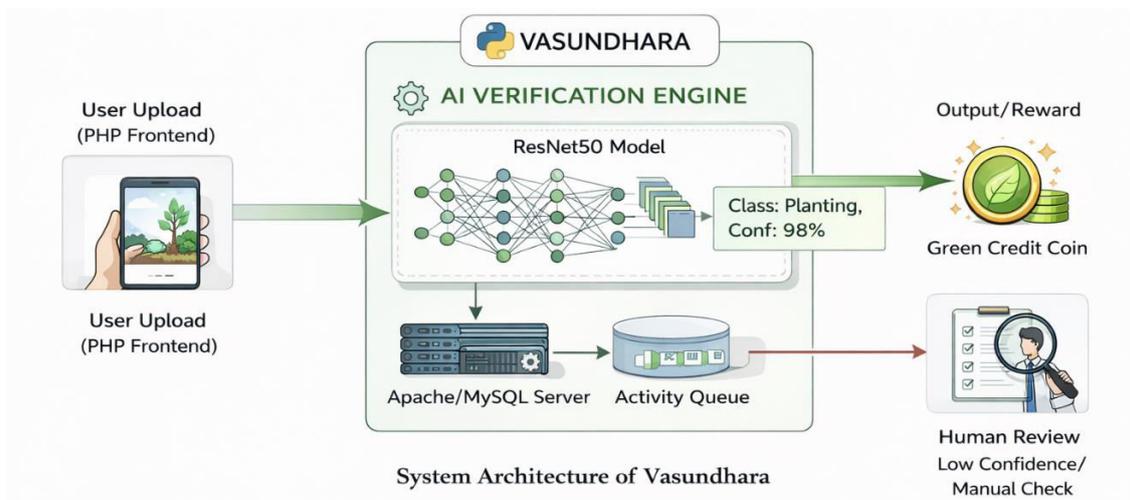


Figure 1: System Architecture of Vasundhara ML-Based Verification Framework

Figure 1 shows the system architecture of the proposed Vasundhara ML-based verification framework. Each block of the system is explained below along with their interconnections:

1. User Upload (PHP Frontend)

Users upload images of environmental activities (e.g., tree plantation, cleanup) through a PHP-based interface. This module collects user data and forwards it to the backend.

2. Apache/MySQL Server

Uploaded images are stored, and related data is recorded in the MySQL database. This module manages users, activities, rewards, and system communication.

3. Activity Queue

A queue system handles pending verification requests, ensuring organized, sequential, and scalable processing during high traffic.

4. ML Verification Engine (ResNet50)

The core engine uses a ResNet50-based CNN with transfer learning to extract features and classify the uploaded images into activity types.

5. Prediction and Confidence Score

The model outputs a predicted activity label along with a confidence score, indicating prediction reliability.

6. Decision Making

- High confidence: Activity is automatically approved and reward points are assigned.
- Low confidence: Activity is sent for manual verification.

7. Dashboard Update

The final result is stored in the database and displayed on the user dashboard, showing status, points, badges, and activity history.

Vasundhara Dataset

The dataset used in this work was created specifically for the Vasundhara project to train and evaluate the proposed machine learning-based environmental activity verification system. The dataset consists of images collected from various online sources and manually curated to represent four different types of environmental activities.

The dataset is organized using a directory-based labeling approach, where the folder names represent the corresponding class labels. The dataset is divided into training and validation sets using a standard train/validation split strategy.

The dataset is stored in the following directory structure:

The dataset is organized as:

- train/ – used for training the model
- val/ – used for validation and performance evaluation

Each subfolder inside these directories represents a class label.

The four activity classes used in this dataset are:

- **cleanup** – clean-up drive / litter pickup activities
- **cycling** – cycling activity images
- **planting** – tree plantation and gardening activities
- **recycling** – recycling and waste segregation activities

The dataset mainly consists of image files in .jpg and .jpeg formats captured under different lighting conditions, backgrounds, and camera qualities to improve the robustness of the model.

Dataset Distribution

The dataset is divided into training and validation sets in approximately 80:20 ratio. The detailed distribution of images is shown in Table X.

Activity Class	Training Images	Validation Images	Total Images
Cleanup	240	60	300
Cycling	240	60	300
Planting	240	60	300
Recycling	240	60	300
Total	980	240	1200

Table 1: Vasundhara Dataset Distribution

Image Pre-processing

Since the collected images vary in resolution, scale, and lighting conditions, several pre-processing steps are applied before training the model. All images are resized to the fixed input resolution required by ResNet50 and pixel values are normalized to improve training stability. In addition, data augmentation techniques such as random rotation and horizontal flipping are applied during training to reduce overfitting and improve the generalization capability of the model.

These pre-processing and augmentation steps enhance the robustness of the proposed verification system when applied to real-world images captured under diverse conditions.



Figure 2: Sample Images from Vasundhara Dataset

Figure 2 shows representative sample images from the Vasundhara dataset used for training and validation of the proposed machine learning model. The figure includes examples from four activity classes, namely cleanup, cycling, planting, and recycling. These images were collected under different lighting conditions, backgrounds, and camera qualities in order to make the dataset more diverse and realistic. Such variation in the dataset helps the model learn robust and generalized visual features, thereby improving the reliability of the classification system.

IV. MODEL ARCHITECTURE AND TRAINING PIPELINE

To identify a suitable model for reliable environmental activity classification, a staged experimental evaluation was conducted using multiple deep learning architectures with progressively improved datasets. The objective was to study the impact of both model capacity and dataset quality on classification performance.

In the first stage, a lightweight MobileNetV2-based model (denoted as MobileNetV2_v1) was trained on a small dataset of 300 images to establish a baseline. Although computationally efficient, this model achieved an accuracy of only 58%, which was insufficient for dependable verification.

In the second stage, the dataset size was increased to approximately 1,400 images and the same architecture was retrained. However, the presence of watermarked and low-quality images limited the learning effectiveness, resulting in only a marginal improvement in accuracy to around 60%. This experiment highlighted that dataset quality is as critical as dataset size.

In the final stage, the dataset was carefully cleaned and curated, resulting in a high-quality dataset of 1,200 images. A deeper ResNet50-based convolutional neural network was then employed using transfer learning. Owing to its stronger feature extraction capability, the ResNet50 model achieved a significantly improved accuracy of approximately 94%, and was therefore selected as the final model for the proposed system. A summary of the evaluated models and their performance is presented in Table 2.

Model	Dataset Size	Dataset Quality	Accuracy (%)
MobileNetV2_v1	300	Raw	58
MobileNetV2	1400	With Watermarks	60
ResNet50 (Proposed)	1200	Cleaned Dataset	94

Table 2 :ML Model Report

4.1 Final Model Architecture (ResNet50)

The final system employs a ResNet50 deep convolutional neural network using a transfer learning strategy. The network is initialized with weights pre-trained on the ImageNet dataset, enabling the model to exploit previously learned generic visual features and improve convergence on the target task.

During training, the convolutional base of ResNet50 is frozen to preserve these learned representations. On top of the base network, a Global Average Pooling layer is added, followed by a fully connected dense layer with ReLU activation. A dropout layer is incorporated to reduce overfitting. The final classification layer is a dense layer with Softmax activation, where the number of output neurons corresponds to the number of activity classes

4.2 Training Strategy

The model is trained using the training subset, while the validation subset is used to monitor performance and control overfitting. During training, only the newly added classification layers are optimized, while the convolutional base of ResNet50 remains frozen. This approach reduces training time and improves generalization on limited data.

The categorical cross-entropy loss function is used in combination with the Adam optimizer. Model performance is evaluated using standard metrics including classification accuracy, training and validation loss curves, confusion matrices, and classification reports.

V. RESULTS AND DISCUSSION

The performance of the proposed Vasundhara environmental activity verification framework is evaluated using three different deep learning models developed at successive stages of the study. The evaluation is conducted using standard performance metrics including classification accuracy, training and validation loss, confusion matrices, and classification reports.

The objective of this experimental analysis is to investigate the impact of dataset size, dataset quality, and model architecture on the overall classification performance, and to justify the selection of the final ResNet50-based model for deployment within the proposed framework.

5.1.3 Proposed ResNet50 — Classification Report Table

Class	Precision	Recall	F1-score	Support
Cleanup	0.92	0.93	0.92	58
Cycling	1.00	0.95	0.97	59
Planting	0.91	0.97	0.94	60
Recycling	0.98	0.95	0.97	61
Accuracy			0.95	238
Macro Avg	0.95	0.95	0.95	238
Weighted Avg	0.95	0.95	0.95	238

Table 3: Classification Performance of Proposed ResNet50 Model

Table 3 presents the classification performance of the proposed ResNet50-based model trained on the cleaned and curated dataset of 1,200 images. The model achieves a high overall accuracy of 94.96%. The precision, recall, and F1-score values are consistently high across all four classes, indicating stable and well-balanced classification performance. These results confirm that the combination of a deeper ResNet50 architecture and a high-quality dataset significantly improves both the robustness and the reliability of the proposed verification system.

5.1.4 FINAL COMPARISON TABLE

Model	Dataset Size	Accuracy (%)
MobileNetV2_v1	300	58.40
MobileNetV2_v2	1400 (with watermarks)	59.24
ResNet50 (Proposed)	1200 (cleaned)	94.96

Table 4: Overall Performance Comparison of All Models

Table 4 summarizes the overall performance comparison of all three evaluated models. It can be clearly observed that the proposed ResNet50-based model significantly outperforms both MobileNetV2-based baselines. This comparison demonstrates that both increased model capacity and improved dataset quality play a crucial role in achieving high and reliable classification accuracy for the proposed application.

5.2 ResNet50 (Proposed) — Confusion Matrix

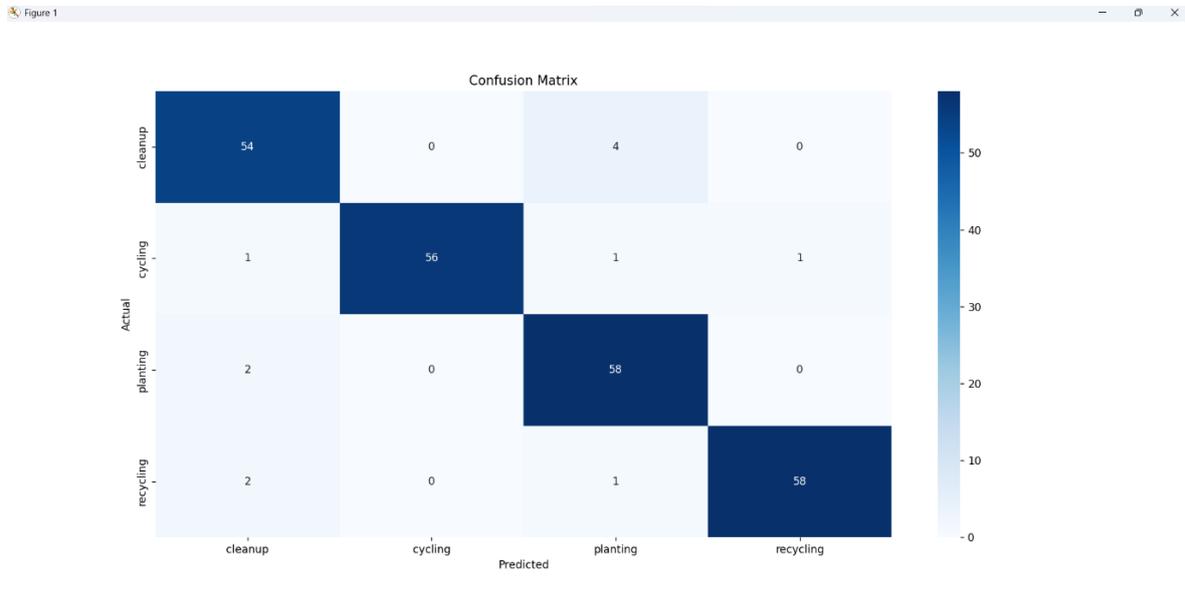


Figure 3: Confusion Matrix of the Proposed ResNet50 Model

Figure 3 presents the confusion matrix of the proposed ResNet50-based classification model. Most samples are correctly classified and concentrated along the diagonal, with only a very small number of misclassifications. This indicates strong class separability and stable predictive behavior. The result further confirms the effectiveness of the ResNet50 architecture when trained on the cleaned dataset and justifies the high classification accuracy of 94.96%.

5.3 Proposed ResNet50 — Accuracy & Loss Curves

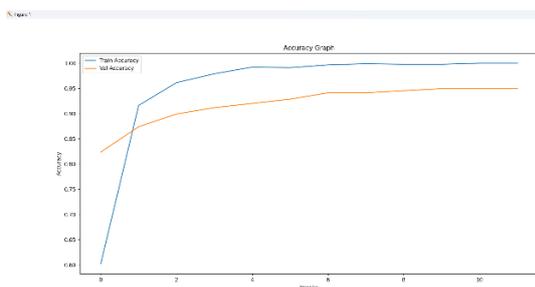


Figure 4: Training and Validation Accuracy Curve of the Proposed ResNet50 Model

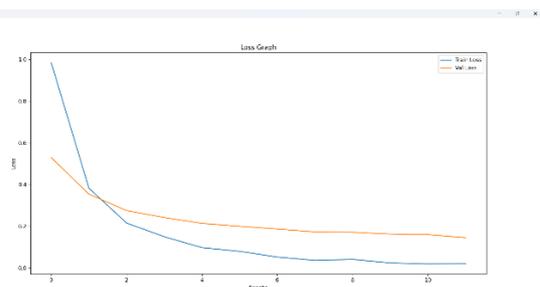


Figure 5: Training and Validation Loss Curve of the Proposed ResNet50 Model

Figures 4 and 5 present the training and validation accuracy and loss curves of the proposed ResNet50-based model. Both training and validation accuracy increase steadily and converge to a high value close to 95%. At the same time, the training and validation loss decrease consistently, indicating stable convergence behavior and good generalization performance with minimal overfitting.

VI. CONCLUSION

This paper presented **Vasundhara**, an AI-driven framework for automated verification and gamification of environmental activities. By integrating a web-based platform with a ResNet50-based deep learning verification model,

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the proposed system enables reliable and scalable validation of activities such as tree plantation, cleanup drives, cycling, and recycling, thereby ensuring transparency in the allocation of green credits.

The experimental results demonstrate that the proposed approach achieves high verification accuracy and stable performance, confirming its suitability for real-world deployment. The integration of an AI-based conversational assistant further improves user interaction and usability of the platform. Overall, the proposed framework provides a practical and technology-driven solution for promoting sustained public participation in environmental sustainability initiatives.

VII. FUTURE SCOPE

In future work, the Vasundhara framework can be extended into a large-scale, institutionally adopted environmental verification platform. One possible direction is integration with government agencies or municipal bodies to enable official recognition and certification of verified environmental activities, thereby improving trust and large-scale adoption.

The platform can also be expanded to support partnerships with non-governmental organizations and private organizations for providing real-world incentives linked to earned green credits. From a technical perspective, future enhancements may include the addition of new activity categories, support for video-based and location-aware verification, and the incorporation of real-time monitoring mechanisms to further improve reliability and misuse prevention.

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