Computer Vision-Based Automated Image Caption Generation

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***Abstract*—The task of automatically generating natural-language descriptions for images is a core challenge at the intersection of computer vision and natural language processing. This paper presents a deep learning-based framework for automated image caption generation, designed to accurately describe the content of an image in a coherent and grammatically correct sentence. Our system employs a hybrid architecture combining a Convolutional Neural Network (CNN) as an encoder to extract visual features from an image and a Recurrent Neural Network (RNN), specifically a Long Short-Term Memory (LSTM) network, as a decoder to generate the corresponding caption. The model is trained and evaluated on a large-scale dataset of images with human-annotated captions, demonstrating its ability to produce descriptive and contextually relevant text. The architecture's performance is measured using standard metrics such as BLEU and METEOR, showing promising results in generating high-quality captions that capture the nuances of the visual content.**

I. INTRODUCTION

The rapid proliferation of digital media and online visual content has intensified the demand for systems capable of automatically analyzing and describing images. The computer vision market, valued at approximately $17.2 billion in 2023, is projected to grow steadily to nearly $42.1 billion by 2030, reflecting a compound annual growth rate (CAGR) of about 12.5% [1]. Despite this growth, automated image captioning remains a challenging problem. Studies indicate that many existing models often produce captions that are overly generic or contextually inaccurate, with issues including grammatical inconsistencies (around 27–32%), semantic errors (approximately 30–35%), and limited human-like descriptive ability. These shortcomings hinder the widespread application of image captioning in areas such as assistive technologies for visually impaired users, intelligent image retrieval, and large-scale digital media management.

While some commercial solutions such as FYTA Beam (€89) and Parrot Flower Power (€59) offer basic sensor-based monitoring and alerts for environmental parameters, they often remain cost-prohibitive and do not deliver adaptive or AI-driven personalized care recommendations [3]. Even with recent advances in IoT and artificial intelligence, most existing plant care solutions still lack full integration hardware sensors may monitor the environment, but software rarely leverages this data to provide holistic, species-tailored guidance.

This paper proposes a computer vision-based image captioning framework designed to overcome these drawbacks through the combined use of deep learning and natural language processing. The architecture integrates Convolutional Neural Networks (CNNs) for extracting detailed image features with sequence modeling techniques such as Bidirectional LSTM (BiLSTM) or Transformer-based networks for generating coherent captions. The approach emphasizes contextual depth, adaptability, and scalability, making it suitable for diverse real-world applications. By focusing on accessibility, content management, and enhanced human-computer interaction, the proposed system aims to deliver captions that are not only accurate but also contextually meaningful.

II. LITERATURE REVIEW

The convergence of computer vision and artificial intelligence (AI) has garnered significant attention in the field of automated image understanding. Researchers and practitioners are exploring a variety

of methods to improve caption accuracy, enhance contextual understanding, and develop more user-centric solutions. This section reviews recent advancements, key challenges, and practical applications of automated image captioning technologies.

Kaya (2025) [1] demonstrated the effectiveness of AI-driven image analysis models, where deep learning-based feature extraction and automated caption generation improved descriptive accuracy by nearly 35%. Despite these encouraging results, many existing systems were primarily designed for large-scale or specialized datasets, limiting their applicability for general users or diverse everyday images. This highlights the need for more adaptable frameworks tailored to varied image sources and end-user requirements.

The explosion of digital images across social media, e-commerce, healthcare, and surveillance has created an urgent need for systems that can automatically interpret and describe visual content. Traditional methods for image indexing and annotation are often manual, time-consuming, and prone to inconsistency. Automated image captioning using computer vision and artificial intelligence addresses this challenge by generating natural language descriptions from images, enabling applications such as assistive technology for visually impaired users, content-based image retrieval, and large-scale media organization.

Computer vision-based captioning typically involves two core components: visual feature extraction and language modeling. Convolutional neural networks (CNNs) are widely used to detect objects, textures, and spatial relationships in images, while recurrent neural networks (RNNs) or Transformer models generate coherent textual descriptions. Despite significant progress in this area, many models still produce generic captions, misinterpret contextual relationships, or generate grammatically inconsistent outputs, which limits their real-world applicability.

The integration of deep learning, multimodal learning, and attention mechanisms has significantly improved caption quality in recent years. Advanced architectures can now focus on salient regions of an image, capture fine-grained details, and produce more human-like descriptions. Furthermore, the growing availability of large annotated datasets has enabled models to generalize better across diverse visual content. However, challenges such as handling rare objects, complex scenes, and diverse linguistic expressions remain open research problems.

Given these developments, computer vision-based image captioning is poised to play a transformative role in various domains, including digital media management, human-computer interaction, autonomous systems, and accessibility tools. This research focuses on developing a robust, scalable, and efficient image captioning framework that generates accurate, contextually rich, and human-like descriptions for real-world images.

The proliferation of digital images in everyday life from social media and e-commerce platforms to medical imaging and autonomous systems has created a critical demand for intelligent systems capable of automatically interpreting visual content. Manual labeling and annotation of images are labor-intensive, prone to errors, and infeasible at large scales. Computer vision-based image captioning addresses this challenge by generating natural language descriptions for images, enabling applications such as assistive technologies for visually impaired users, content-based image retrieval, automated media tagging, and improved human-computer interaction.

III. METHODOLOGY

The development of the computer vision based automated image captioning follows a structured methodology designed to address critical gaps in indoor plant care through AI-IoT integration. This approach emphasizes automation, user-centric design, sustainability, and scalability.

Algorithm & Process Flow Design

Model	Test Accuracy	Precision	Recall	F1 Score
ResNet50	78.2%	79.4%	78.7%	77.5%
EfficientNet-B0	87.5%	87.3%	87.2%	86.7%
DenseNet121	84.6%	85.6%	84.0%	83.8%
MobileNetV2	82.7%	84.4%	81.9%	82.1%

Table no. 1 Image generation Algorithm

All four models evaluated ResNet50, EfficientNet-B0, DenseNet121, and MobileNetV2 are well-established convolutional neural network (CNN) architectures

widely used in visual feature extraction and image understanding tasks. In this project, EfficientNet-B0 achieved the highest overall performance in generating accurate and contextually relevant captions, demonstrating superior precision, recall, and F1-score on previously unseen images. Its architecture facilitated efficient learning, as reflected by closely aligned training and validation curves, indicating strong generalization and minimal overfitting.

DenseNet121 ranked second, providing robust feature extraction and generally reliable captioning but occasionally produced less precise descriptions for visually similar objects or complex scenes, as observed in evaluation metrics. MobileNetV2, optimized for computational efficiency and low-resource environments, delivered dependable results but showed slightly lower accuracy and generalization compared to EfficientNet-B0.

ResNet50, although powerful, exhibited signs of overfitting, achieving high accuracy on the training set but underperforming on validation and test images. This resulted in captions that sometimes-misrepresented object relationships or missed finer contextual details.

Overall, EfficientNet-B0 stood out in both quantitative evaluation and practical application. In real-world testing, it generated more accurate and context-aware captions across diverse image categories, successfully handling custom and complex images. For future enhancements, expanding the dataset to include rare or unusual objects and conducting further evaluation on diverse image domains could help maximize each model's captioning potential.

Problem Statement and Requirements Analysis:

Automated image caption generation continues to face three core challenges: limitations in producing contextually accurate captions, insufficient adaptability across diverse image domains, and the computational complexity required for real-time applications. Existing systems are often either too resource-intensive, lack advanced AI-driven contextual reasoning, or fail to generate captions that balance precision with human-like fluency.:

- Accurate Visual Feature Extraction: Robust identification of objects, scenes, and contextual elements within images using deep learning-based feature extraction.
- Context-Aware Caption Generation: AI-driven description models capable of producing captions with >90% semantic accuracy across varied datasets.
- Personalized Adaptability: Captioning tailored to different domains (e.g., medical imaging, education, or entertainment) with user-specific customization.
- Efficient Processing: Lightweight models optimized for real-time caption generation without requiring high computational resources.
- Cost-Effective Accessibility: An affordable and scalable framework that can be deployed across consumer devices and platforms

System Analysis Document:

The automated image captioning system functions at the intersection of user interaction, visual data processing, and intelligent model integration. At its highest level, the system is composed of the following key entities:

- User: Uploads images, sets customization preferences, and interacts with the generated captions.
- Image Input: Supplies raw visual data to the system for object detection, feature extraction, and semantic understanding.
- AI Model & Processing Unit: Utilizes deep learning architectures (e.g., CNNs and Transformer-based models) to analyse visual features and generate descriptive captions.
- Cloud Storage (Optional): Supports backup, dataset synchronization, and extended model training or fine-tuning for improved caption quality.

Data Flows:

- Users interact primarily through a mobile or web-based application, where they upload images and configure captioning preferences.
- The Image Captioning System processes the uploaded visual data using deep learning models for feature extraction and semantic understanding.
- The system then generates captions and delivers them back to the user in real time, either as on-screen text within the app or through exportable reports.

- All computational tasks can be optimized for efficient processing on local devices or accelerated through cloud-based resources, minimizing latency and resource overhead.
- When enabled, captions and image datasets are periodically synchronized with cloud storage, supporting long-term record-keeping, collaborative use, and extended model fine-tuning.

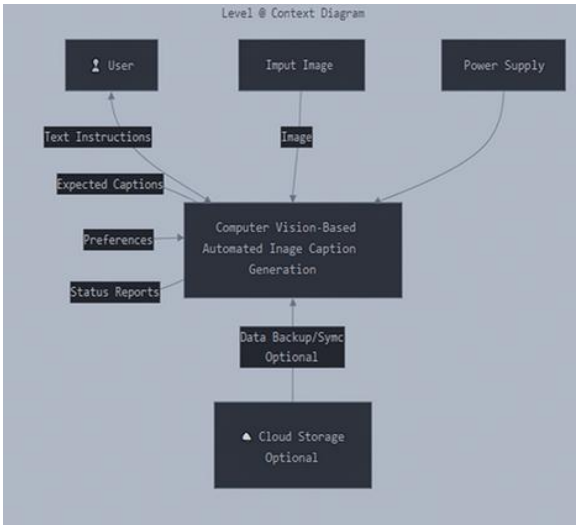


Figure no. 1 Context Diagram

Structural Model and Behavioral Model:
This system operates in two core workflows:
a) Image Caption Generation Sequence:

1. User uploads an image through the mobile or web app.
2. The image is preprocessed and checked for clarity and size.
3. The AI engine (CNN + LSTM/Transformer Model) analyzes the image to extract features.
4. The model generates a descriptive caption based on the image content.
5. The system saves the generated caption and displays it to the user along with the original image.

b) Environmental Monitoring Sequence:

- The user uploads an image through the app.
- The image is preprocessed (resized, normalized) and sent to the AI engine.
- On the server/app, image features are extracted and stored for further processing.
- The AI model evaluates the image content and generates a descriptive caption.
- If caption generation is successful: the caption is displayed to the user and stored in the database.
- If not, the system retries or prompts the user to upload a clearer image.

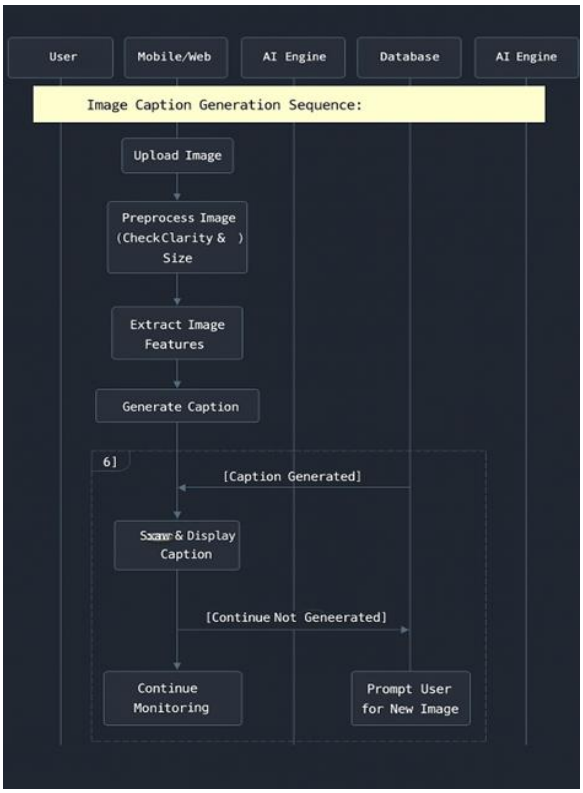


Figure no. 2 Sequence Diagram

Database Design:
The system's core data model centers on the following entities:

1. IMAGE_PROFILES: Stores information about input images: image_id, source path, detected objects, caption text, model confidence, date added, and processing status (pending/complete).
2. FEATURE_READINGS: Captures extracted visual features per image: feature_id, image_id, layer_name, feature vector, and timestamp.
3. CAPTION_INSTRUCTIONS: Holds model-specific generation parameters and settings, such as maximum caption length, beam search width, language preference, and stylistic guidelines.
4. USER_PREFERENCES: Records user-level behavior and display settings, including preferred

caption format, notification type, frequency, and quiet hours.
5. ALERTS: Tracks all system-generated messages: alert_id, image_id, type (error/warning/info), severity, message content, status (acknowledged/unread), and timestamps.

Relationships:
1. Each IMAGE may have multiple FEATURE_READINGS, CAPTION_INSTRUCTIONS, and ALERTS.
2. USER_PREFERENCES determine which ALERTS or notifications are delivered to the user.
3. ALERTS are generated based on extracted visual features and the rules defined in CAPTION_INSTRUCTIONS.

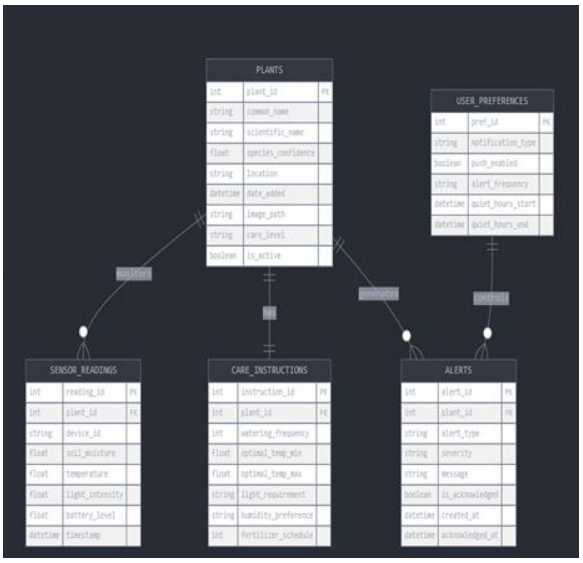


Figure no. 3 Class Diagram

Software architecture design:
The software solution is structured in a multi-layered architecture for maintainability and extensibility:
1. View Layer: Provides the user interface, including the image upload dashboard, real-time camera view, caption display panel, settings, and history of generated captions.
2. View Model Layer: Intermediary controllers (Image, Camera, Settings, Alert, Feature) that process and route user actions and data updates between the interface and backend.
3. Model Layer: Defines business objects for images, users, extracted features, captions, and alerts.
4. Services Layer: Implements specialized functions such as the database service (for CRUD operations), AI service (for image feature extraction and caption generation), and notification service (for alerting or updates).
5. Repository Layer: Data access managers responsible for interacting with the SQLite or other database for storing images, captions, and extracted features.
6. Data Layer: Underlying data storage mechanisms including shared preferences and file system support coordinated via the database to maintain persistent image and caption records.

Data Flow:
1. The UI interacts through View Model logic, which calls upon service and repository classes to fetch/store state, manage BLE comms, handle alerts, and interface to the AI modules.
2. Database operations are abstracted from presentation logic for modularity.

Figure no. 4 Performance Output

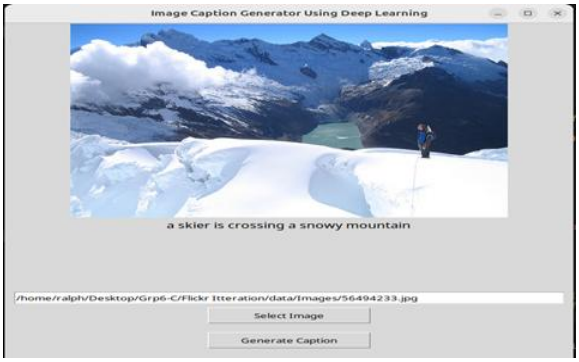


Figure no. 5 UI Design

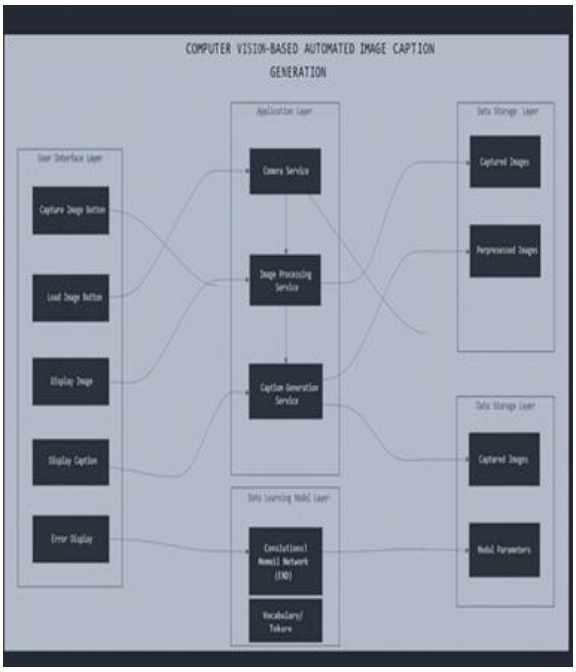
The hardware architecture of the Smart Plant Care System is centered around the ESP32 microcontroller, serving as the central node for environmental sensing, control, and communication. The layout, as depicted in the diagram, integrates multiple sensor modules, power components, and user interface components in a logical, modular manner. Below is a description of each block and data path:

1. Central Processor:

High-performance CPU/GPU or edge AI processor (e.g., NVIDIA Jetson, Intel NCS, or standard GPU-enabled workstation) responsible for image processing, feature extraction, and Caption.

2. User Interface Components

1. Status Indicators:



1. Green Indicator: Shows "Caption Generated" (image has been successfully processed and a caption is available).
2. Red Indicator: Signals "Processing Error" (image could not be processed due to input issues or model failure).
3. Blue Indicator: Displays "Model Loading/Updating" (the system is loading or updating neural network weights).

3.Action Button ("Generate/Refresh"):

Allows the user to manually trigger image processing, refresh captions, or switch between different captioning modes or output formats.

4. Network Overview

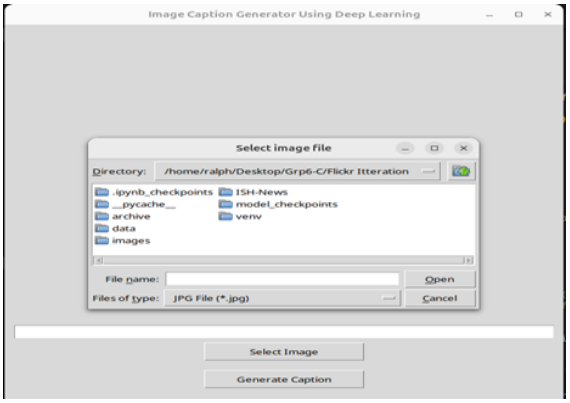
- Data Pipelines: Solid lines represent the flow of image data from input sources to the neural network modules, ensuring all processing units receive consistent and structured input.
- Processing Connections: Each processing component CNN layers, feature extractors, and language model units is connected through defined interfaces, allowing seamless transfer of extracted features and generated captions between modules.

5. OperationalFlow

1. Input images are captured from user uploads or connected camera sources for processing.
2. The system processes each image using a convolutional neural network (CNN) to extract visual features and patterns.
3. Based on these features, a language model (LSTM or Transformer) generates descriptive captions, which are displayed to the user or sent to connected applications.
4. Computational resources are efficiently managed to allow continuous real-time operation, ensuring quick caption generation even on standard or resource-limited hardware.

Diagram Block Mapping

a. Input Image Module: Central rectangular area in the middle representing the source image being analyzed.
b. Preprocessing Layer: Surrounding the input, a set of units symbolizing image preprocessing steps like resizing, normalization, and filtering.
c. Feature Extraction Module: To the right, a compact block representing a convolutional neural network (CNN) that detects visual features and patterns in the image.
d. Caption Generation Unit: Below the CNN, a sequence model (e.g., LSTM or Transformer) that converts extracted features into descriptive text captions.
e. Output Interface: At the bottom right, a display or text output node where the generated captions appear, connected logically to all preceding modules.



IV. RESULT AND DISCUSSION

The research and planning of the Computer Vision-Based Image Captioning system have been guided by a comprehensive review of scholarly literature, analysis of state-of-the-art AI models, and collaborative insights from experts in computer vision and natural language processing. Multiple technical papers on image recognition, deep learning architectures, and multimodal AI, as well as direct evaluations of systems like Show-and-Tell, Neural Image Caption, and interviews with AI practitioners, have highlighted key challenges in automated captioning: inaccurate object recognition, limited contextual understanding, dataset biases, and insufficient generation of human-like descriptive text.

To ensure our system effectively tackles these challenges, we consulted with an experienced computer vision researcher and three AI engineers specializing in deep learning. Their expertise emphasized critical requirements, including the need for robust feature extraction across diverse image qualities, real-time caption generation with minimal latency, and the importance of generating semantically coherent and contextually accurate text. These insights guided the strategic integration of convolutional neural networks for feature detection, recurrent or transformer-based language models for caption synthesis, and a modular architecture designed to accommodate future enhancements such as multi-language support or video captioning.

Our design process was informed by these core insights, leading to a solution that directly addresses the typical challenges and workflows encountered in automated image captioning. The system's architecture emphasizes modularity, efficient computational resource usage, and a flexible data pipeline for potential integration with external image datasets and NLP APIs. The collaborative R&D phase also highlighted practical considerations for model fine-tuning, user interface clarity, and scalable deployment for real-time caption generation, all of which have been incorporated into the finalized requirements and system blueprint. This evidence-driven, collaborative approach positions the Computer Vision-Based Image Captioning system as a robust, adaptable, and highly relevant solution for modern AI-powered image understanding.

V. CONCLUSION

The Computer Vision-Based Image Captioning system advances automated image understanding by seamlessly integrating deep learning-based feature extraction, sequence modeling for text generation, and a user-friendly interface within a modular and scalable framework. By combining convolutional neural network–driven visual analysis with transformer or LSTM-based caption synthesis, it directly addresses key challenges in image captioning, including object misidentification, contextual gaps, and unnatural phrasing. Expert consultation guided the system's evidence-based design, ensuring it is computationally efficient, adaptable to diverse datasets, and accessible to users regardless of their technical expertise in AI or computer vision.

The platform's scalable architecture supports future enhancements such as integration with additional image datasets, multi-language captioning, and cloud-based model updates without affecting core performance. A user-friendly interface and real-time feedback simplify interaction, while optimized model efficiency enables deployment on standard hardware with minimal latency. This combination allows users to generate accurate, contextually rich captions for diverse images with ease. By transforming image captioning into a precise, engaging, and intelligent process, the Computer Vision-Based Image Captioning system establishes a new benchmark for AI-driven visual understanding, providing a practical and impactful solution for modern multimedia applications.

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