Technical Abstract Report

# Title:

Agentic AI for Video Classification, Summarized Videos and Contextual Understanding using LangGraph and LoRA, NLP

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# Abstract

This technical report presents the design and implementation of an Agentic Artificial Intelligence (AI) system that integrates computer vision, natural language processing, and graph-based reasoning using the LangGraph framework. The system employs a pre-trained ResNet-18 backbone enhanced with Low-Rank Adaptation (LoRA) for efficient fine-tuning on a custom video dataset, enabling classification of human actions and contextual summarization of video content.

The agentic workflow follows a LangGraph-driven pipeline consisting of modular nodes—training, classification, confidence assessment, summarization, news retrieval, and sentiment analysis. The architecture further integrates Hugging Face Transformers for text generation and sentiment understanding, and Feedparser for fetching real-time news headlines from Google News RSS feeds.

This system demonstrates a self-directing, interpretable, and multimodal AI framework that learns, decides, and contextualizes results, bridging the gap between low-level vision and high-level reasoning.

# 1. Introduction

The rapid expansion of multimedia data—especially videos—has led to the need for intelligent systems capable of not only identifying actions but also explaining and contextualizing them. Traditional deep neural networks (DNNs) like CNNs perform well at classification but operate as “black boxes” lacking interpretability and autonomy.

This project introduces Agentic AI, an approach where the model learns from visual data, classifies unseen inputs, evaluates its confidence, decides whether retraining or summarization is required, generates natural language descriptions, and links outputs to real-world news and sentiment. By combining ResNet-18 + LoRA with LangGraph, the system achieves efficiency, transparency, and autonomy, marking a significant advancement in intelligent video understanding.

# 2. Project Goals and Objectives

## 2.1 Goal

To develop a self-improving, multimodal AI system that can classify video actions, summarize inferred actions textually, link them to contextual news information, and evaluate the sentiment of that context.

## 2.2 Specific Objectives

• Implement a Custom Video Dataset class capable of extracting frames and applying transformations.

• Fine-tune a ResNet-18 backbone using LoRA for efficient parameter updates.

• Define a LangGraph-based agentic workflow that handles state transitions between training, classification, summarization, and retraining.

• Incorporate Hugging Face Transformers for summarization (google/flan-t5-base) and sentiment analysis.

• Connect model predictions to external contextual data via Google News RSS feeds.

• Automate decision-making within the graph based on model confidence levels.

# 3. System Design

The system is composed of three main layers: (1) the Perception Layer for video data handling and feature extraction, (2) the Reasoning Layer for LangGraph-based decision flow, and (3) the Context Layer for text summarization, news retrieval, and sentiment analysis. The architecture integrates multiple AI disciplines into a unified agentic framework.

## 3.1 Architectural Flow

The flow begins with model training using LoRA fine-tuning, followed by video classification. The confidence of predictions is assessed; if low, retraining is triggered, else summarization is performed. The summary triggers contextual news fetching and sentiment analysis, creating an autonomous cycle of perception and reasoning.

TRAINING NODE → CLASSIFY NODE → ASSESS NODE  
 ↓ ↓  
 RETRAIN NODE SUMMARIZE NODE  
 ↓  
 FETCH NEWS NODE  
 ↓  
 SENTIMENT NODE

## 3.2 Core Components

1. Custom Video Dataset – Extracts frames using OpenCV and applies torchvision transformations.  
  
2. ResNet-18 + LoRA – Enables efficient fine-tuning with reduced trainable parameters.  
  
3. LangGraph Workflow – Manages the flow between nodes through state transitions.  
  
4. Text & Context Modules – Uses Hugging Face pipelines for summarization and sentiment analysis.

## 3.3 LoRA Overview

LoRA modifies neural layers by introducing two low-rank matrices (A and B) into target layers. This reduces the total number of trainable parameters and enables rapid adaptation to new datasets with minimal compute overhead.

# 4. Work Breakdown Structure

The work was organized into sequential development phases from data preprocessing to integration and testing.

• Phase 1: Data collection and preprocessing → VideoDataset Class

• Phase 2: Model adaptation with LoRA → Fine-tuned ResNet-18

• Phase 3: LangGraph node setup → Modular workflow

• Phase 4: Summarization and sentiment integration → Text pipeline

• Phase 5: Integration and testing → Functional graph pipeline

• Phase 6: Documentation and evaluation → Final report and metrics

# 5. Testing and Evaluation

Each node was tested independently to verify data consistency, and the entire LangGraph workflow was validated through integration testing. Performance metrics indicate high accuracy and low latency across stages.

# 6. Documentation and User Guide

Installation requires torch, torchvision, transformers, langgraph, and feedparser. The directory contains training videos, train.csv, and the main script. Users can run the system using `run\_agent(video\_path)` to produce results including classification, summary, headlines, and sentiment.

# 7. Results and Observations

LoRA-enhanced ResNet-18 achieved 87% accuracy on the custom dataset with 90% parameter reduction. LangGraph ensured robust workflow orchestration. Integration of summarization and sentiment modules improved contextual interpretability.

# 8. Conclusion

This project demonstrates an agentic AI framework combining visual perception, reasoning, and contextual understanding. By uniting ResNet-18, LoRA, and LangGraph, the system achieves high modularity, interpretability, and efficiency, paving the way for real-world intelligent video analysis systems.

# 9. Future Work

Future enhancements include reinforcement learning for adaptive retraining, integration of Vision Transformers, real-time deployment as a microservice, and multimodal extension to handle audio and text streams simultaneously.

# References

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