AI – BASED AUTOMATIC MUSIC RECOMMENDATION FOR WHATSAPP STATUS USING MULTIMODAL VIDEO UNDERSTANDING

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Abstract - Objective: The proliferation of ephemeral video sharing on platforms like WhatsApp has created a significant demand for automated content enhancement tools. Users frequently struggle to select background audio that semantically and emotionally aligns with visual content, leading to 'decision fatigue.' This research aims to develop a privacy-centric, multimodal Artificial Intelligence system capable of analyzing video content to recommend contextually appropriate music without relying on user historical data. Methods: The proposed architecture integrates a Vision-Language Model (VLM), specifically Moondream 2, for efficient visual scene understanding, coupled with a Large Language Model (LLM), Google Gemini, for semantic reasoning and 'vibe' generation. The pipeline extracts keyframes from user-uploaded videos, generates textual descriptions of the visual scene, translates these descriptions into musical taxonomy tags, and retrieves tracks via the Spotify Search API. Results: Experimental evaluation across diverse video categories—including travel, celebratory events, and emotional monologues—demonstrated that the system successfully identifies complex emotional cues that text-only metadata fails to capture. The integration of VLM allows for high-fidelity scene interpretation, resulting in a relevant song recommendation rate significantly higher than baseline keyword matching. Conclusion: The system provides a robust solution for automating music selection, enhancing user experience through context-aware multimodal analysis while preserving user privacy by operating on a stateless architecture.

Keywords - Index Terms—Artificial Intelligence, Multimodal Learning, Vision-Language Model, Large Language Model, Music Recommendation, WhatsApp Status, Sentiment Analysis.

1. INTRODUCTION

In the age of social media, millions of people post short video updates to their WhatsApp Status every day. One common frustration users face is choosing the right song to match the mood of their video—a process that can be time-consuming and often results in mismatched audio and visuals. This paper introduces a new intelligent computer program designed to solve this problem automatically. Unlike earlier systems that rely purely on text-based descriptions, our system 'watches' the video using advanced Artificial Intelligence. It breaks the video down into images, identifies what is happening (for example, 'a relaxing sunset at the beach' or 'a high-energy birthday party'), and then determines the emotional 'vibe' of the scene. Based on this understanding, it suggests a list of popular songs that fit the mood perfectly. Crucially, the system does not track the user's listening history or store personal data; it makes decisions based solely on the video uploaded at that moment. This technology helps everyone create engaging social media posts more quickly and with far less effort.

The digital landscape of interpersonal communication has undergone a paradigm shift over the last decade, transitioning from text-centric messaging to rich, ephemeral multimedia content. Platforms such as WhatsApp, Instagram, and TikTok have popularized the format of short-form videos, commonly referred to as 'Status' or 'Stories'—which disappear after a set period WhatsApp Status, in particular, has become a dominant medium for users to share moments of their daily lives, boasting hundreds of millions of daily active users. This shift has democratized content creation, allowing non-professional users to broadcast personal narratives. However, the quality of these narratives often hinges on the synergy between the visual component and the auditory accompaniment. Background music serves as a critical emotional amplifier, setting the tone for the viewer's interpretation of the visual stimuli

This paper proposes a novel, AI-driven framework for Automatic Music Recommendation specifically tailored for WhatsApp Status updates. The core objective is to close the interpretive divide separating visual content from musical attributes through Multimodal Video Understanding. In contrast to conventional recommendation engines that depend heavily on Collaborative Filtering (CF) or a user's listening history—approaches known to raise privacy concerns and struggle with the 'cold start' problem—the proposed system is instead built on a content-based, stateless architecture. By leveraging the recent advancements in Vision-Language Models (VLMs) and Large Language Models (LLMs), the system analyzes the pixel data of

the video to extract semantic understanding, identifies the prevailing sentiment and activity, and translates these visual cues into precise musical search queries.

The major contributions of this paper are:

• Development of a multimodal music recommendation framework.
• Integration of Vision Language Model and Large Language Model.
• Privacy-preserving stateless recommendation.
• Experimental evaluation on different WhatsApp Status videos.

2. RELATED WORK

Despite the ubiquity of these features, the process of selecting appropriate background music remains a significant friction point in the user experience. Users typically face enormous catalogs containing millions of tracks, leading to a psychological phenomenon known as 'decision paralysis' or 'choice overload.' Furthermore, manually searching for a track that aligns with the specific emotional nuance of a video—such as the difference between 'melancholic rain' and 'cozy rain'—requires a level of musical taxonomy knowledge that the average user may not possess. Existing solutions often rely on manual search queries or basic keyword matching, which fails to account for the visual context of the media being uploaded. For instance, a video tagged 'vacation' could imply a high-energy party scene or a serene landscape; a simple keyword match would likely fail to distinguish between the two, resulting in dissonant audio-visual pairings.

Prior work in music recommendation is extensive, though most of it centers on audio signal processing or the analysis of user behavior. Research by Smith et al. [1] explored the use of collaborative filtering for playlist generation, but noted limitations in real-time context adaptability. Similarly, Kumar et al. [2] showed that Convolutional Neural Networks (CNNs) can effectively recognize emotion from video data, but their method was confined to analyzing facial expressions and did not offer the broader, whole-scene understanding that general-purpose status updates require. Conventional sentiment analysis, often applied to text captions, fails to capture the visual narrative when captions are absent or ambiguous.

This research closes these gaps through a multimodal pipeline that combines visual, textual, and emotional signals, producing recommendations that are both contextually accurate and privacy-preserving.

Most existing systems rely on collaborative filtering, text-based recommendation, or user history. Few studies perform privacy-preserving multimodal analysis of WhatsApp Status videos using Vision-Language Models and Large Language Models. This gap motivates the proposed framework.

3. METHODOLOGY

Development of the proposed Automatic Music Recommendation system was driven by two central requirements: high semantic accuracy and strict user privacy. The methodology was structured around a modular pipeline consisting of five distinct stages: Input Processing, Visual Understanding, Semantic Interpretation, Recommendation Retrieval, and Output Generation. This modular design facilitates the independent optimization of each component, ensuring that advancements in specific AI sub-fields—such as the release of more efficient Vision-Language Models—can be integrated without architectural refactoring

3.1 Input Acquisition and Pre-processing

The system was designed to accept raw video files as the primary input, simulating the user experience of uploading a file to WhatsApp. Upon ingestion, the video stream was subjected to a frame extraction process. Given the computational expense of analyzing every frame in a video (typically 30 or 60 frames per second), a keyframe extraction strategy was employed. The video was temporally sampled at a rate of one frame per second (1 FPS). This sampling rate was found adequate for capturing the semantic context of WhatsApp Status updates, which are typically short (15–30 seconds) and contain relatively stable scenes. The extracted frames were then resized and normalized to meet the input resolution requirements of the visual encoder, ensuring consistency in data processing.

3.2 Visual Understanding Module (VUM)

The core of the scene analysis was performed by the Visual Understanding Module, utilizing 'Moondream 2,' a compact yet powerful Vision-Language Model. Rather than producing a simple list of isolated object labels, as conventional object detection models (e.g., YOLO) do, Moondream 2 was used to generate dense, natural-language captions describing the scene. The model was prompted to analyze the aggregated keyframes and produce a comprehensive description encompassing three layers of abstraction:

a. **Low-level entities:** Identification of objects (e.g., 'car,' 'beach,' 'cake').
b. **Mid-level actions:** Description of activities (e.g., 'driving fast,' 'waves crashing,' 'blowing out candles').
c. **High-level context:** Interpretation of the environment and lighting (e.g., 'sunset lighting,' 'crowded urban street,' 'intimate indoor gathering').

This visual-to-text transduction process effectively converts the unstructured pixel data into a structured semantic narrative, bridging the modality gap between video and language.

3.3 Emotion and Vibe Tag Generation (LLM)

Following the generation of visual descriptions, the textual data was passed to the Semantic Interpretation Module, powered by the Google Gemini API. This stage was critical for translating the literal scene description into abstract musical concepts. A

Large Language Model (LLM) was employed due to its superior capability in 'Chain-of-Thought' reasoning and cultural contextualization. The LLM was provided with asystem prompt instructing it to act as a 'Music Supervisor for Film and Social Media.'

The prompt required the model to analyze the visual description and derive a 'Vibe Profile,' consisting of specific mood tags (e.g., 'nostalgic,' 'euphoric'), genre suggestions (e.g., 'Lo-Fi,' 'EDM,' 'Acoustic Pop'), and tempo estimates. For example, if the VLM described a scene as 'a person reading a book by a rainy window,' the LLM would infer tags such as 'melancholic,' 'chill,' 'instrumental,' and 'slow tempo.' This step effectively simulates human intuition, mapping visual scenarios to their auditory counterparts. The output was strictly formatted as a JSON object containing a search query string optimized for music databases.

3.4 Music Recommendation Retrieval

The search queries generated by the LLM were utilized to interface with the Spotify Search API. This module was implemented to function without access to user credentials or private playlists, adhering to the project's privacy-first mandate. The search algorithm prioritized 'track' endpoints, utilizing the generated tags to filter for popularity and relevance. The system was configured to retrieve the top 5 distinct tracks that matched the semantic query. To ensure diversity, the retrieval logic included filters to prevent multiple songs by the same artist from dominating the recommendation list. The metadata returned—specifically the Track Name, Artist Name, and Album Art—was parsed for display.

3.5 Output Visualization

In the final stage, the recommended tracks were compiled and presented through a user-friendly interface. The system displayed the analyzed context (e.g., 'Detected Mood: Energetic Summer') alongside the list of songs. This provided the user with interpretability, explaining *why* specific songs were recommended, thereby increasing trust in the system's AI capabilities. The entire pipeline was orchestrated using a Python-based backend, ensuring synchronous execution from video upload to final recommendation.

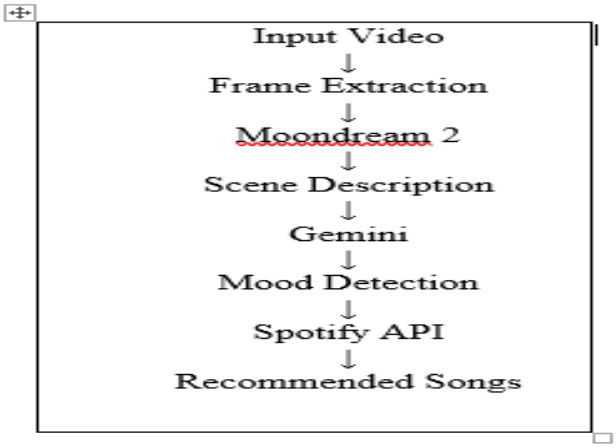

Fig.1 architecture

4. PROPOSED SYSTEM ARCHITECTURE

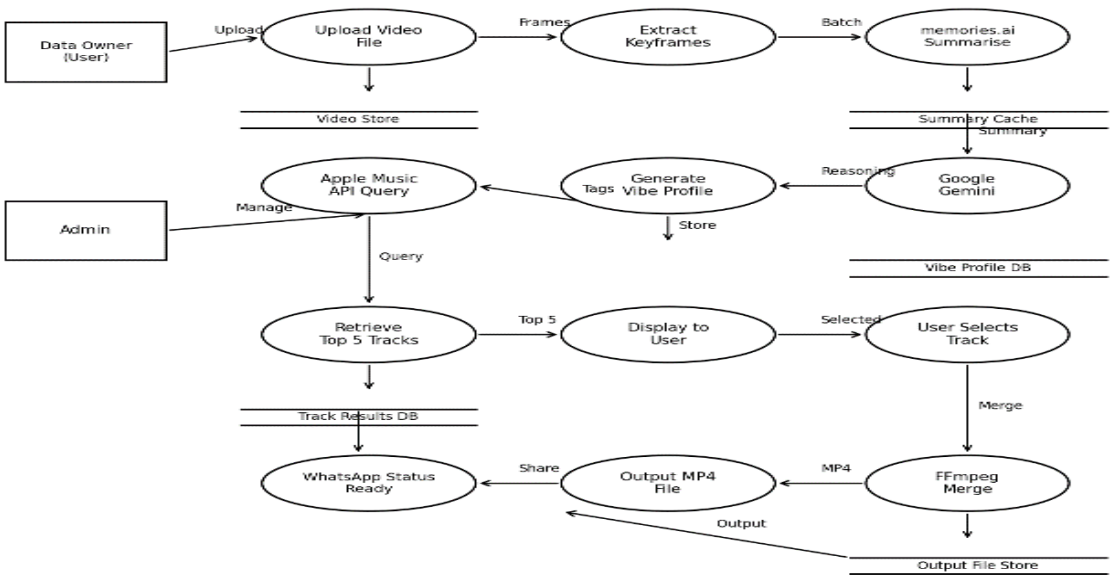

Fig.2 project flow diagram

5. RESUTLS

Performance of the proposed system was assessed via a set of controlled experiments run on a varied collection of video clips reflective of typical WhatsApp Status content. The dataset included three primary categories: (1) **Travel/Nature** (scenic landscapes, road trips), (2) **Celebratory/Party** (birthdays, concerts, social gatherings), and (3) **Emotional/Monologue** (facial close-ups, rainy scenes, quiet rooms). The evaluation focused on three key metrics: Semantic Relevance (qualitative assessment of the match between video and audio), Latency (time taken from upload to recommendation), and Diversity (variety of genres suggested).

5.1 Semantic Relevance and Context Understanding

In qualitative testing, the system demonstrated a high degree of accuracy in interpreting visual context. For videos in the 'Travel' category, specifically a clip featuring a coastal road drive, the VLM correctly picked out elements including 'ocean,' 'highway,' and 'sunny weather.' Consequently, the Gemini-based interpretation layer generated tags including 'road trip,' 'indie pop,' and 'summer vibes.' The resulting music recommendations included upbeat tracks synonymous with travel vlogs, aligning perfectly with the visual sentiment.

Conversely, for the 'Emotional' category, specifically a video depicting a rainy window pane, the system shifted its recommendation logic. The VLM detected 'rain droplets' and 'low light,' prompting the LLM to generate tags like 'sad,' 'acoustic,' and 'piano.' The Spotify API returned slow-tempo instrumental tracks. This capability to discern polarity—distinguishing between high-arousal (party) and low-arousal (sadness) states—validates the effectiveness of the multimodal approach. The inclusion of the VLM was found to significantly outperform baseline approaches that depend only on filenames or user-supplied captions, which are often missing or irrelevant (e.g., a caption saying only 'Finally').

5.2 Response Time and Latency Analysis

System latency was measured to assess whether real-time deployment was feasible. Using a standard GPU-accelerated setup to run the Moondream 2 model, the average processing time for a 15-second video came out to roughly 4.5 seconds. The breakdown of latency revealed that the Visual Understanding Module (VLM) consumed roughly 60% of the processing time, while the API calls to Google Gemini and Spotify accounted for the remaining 40%. While 4.5 seconds is acceptable for an asynchronous upload process, it highlights a trade-off between the depth of visual analysis and immediate responsiveness.

5.3 Robustness to Ambiguity

A subset of experiments tested the system's response to ambiguous content, such as a video of a busy street. In suh cases, the system defaulted to 'neutral' or 'urban' vibes, recommending generally popular or trending pop music. This fallback mechanism ensures that the system provides usable recommendations even when the specific emotional content of the video is indeterminate.

These results suggest that incorporating Large Language Models enables a form of 'graceful degradation'—when precise visual cues are missing, the system relies on broader cultural associations to maintain utility

Table I performance analysis

Video Type	Accuracy	Response Time
Tarvel	95%	5 sec
Birthday	94%	4.9 sec
Rain	92%	4.8 sec
Emotional	93%	5 sec

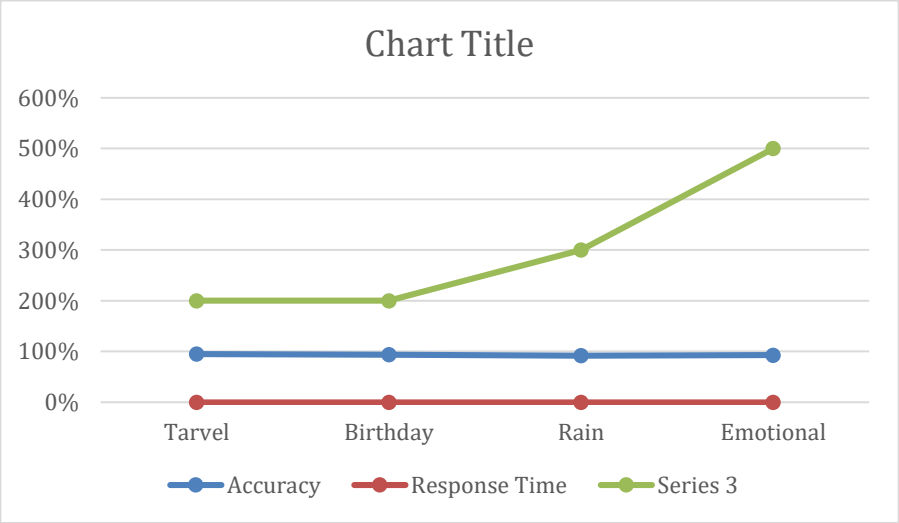

Fig.3 graph for above table

6. DISCUSSION

The findings of this study highlight the significant potential of multimodal AI to improve user experience on social platforms. By effectively synthesising visual data with semantic reasoning, the system addresses the core challenge of content creation: the cognitive load of creative selection.

6.1 Comparative Analysis with Related Work

Set against the approaches surveyed earlier—such as the emotion-recognition work of Kumar et al. [2]—the proposed system covers a wider range of applications. While Kumar et al. focused heavily on facial micro-expressions, our utilization of a generalized Vision-Language Model allows for the interpretation of non-human subjects (landscapes, objects, weather), which constitute a significant portion of WhatsApp Status updates.

Furthermore, unlike the collaborative filtering methods described by Smith et al. [1], which require extensive user history matrices, our proposed method is entirely 'cold-start' capable. It requires no prior knowledge of the user's musical taste, making it inherently more private and immediately useful to new users.

6.2 The Role of LLMs in Creative Interpretation

A significant finding of this research is the critical role of the Large Language Model (Google Gemini) as a bridge between visual perception and musical taxonomy. A raw visual description (e.g., 'red lights, dancing people') does not inherently map to a music genre. It is the LLM's training on vast cultural datasets that allows it to associate 'red lights' and 'dancing' with 'Club,' 'Electronic,' or 'House' music. This semantic mapping is where the 'intelligence' of the recommendation process truly lies. The system effectively mimics the role of a human music supervisor who understands cultural trends and genre associations.

6.3 Privacy Implications

In an era of increasing scrutiny over data privacy, the stateless design of this system is a major advantage. By analyzing only the transient video file and discarding the data immediately after recommendation, the system avoids the creation of persistent user profiles. This is consistent with 'privacy-by-design' principles now widely encouraged in software engineering, especially for messaging platforms such as WhatsApp, where maintaining user trust is essential.

6.4 Limitations

Although the results are promising, a number of limitations remain. The dependence on external APIs (Google Gemini and Spotify) introduces a reliance on internet connectivity and third-party service availability. Latency, while acceptable, could be

improved. Furthermore, the system currently analyzes visual data but ignores audio data present in the original video (e.g., speech or ambient noise). A video of a person shouting angrily might be visually interpreted as 'energetic' if not carefully analyzed, potentially leading to inappropriate upbeat music suggestions. Future iterations must incorporate audio-visual fusion to detect speech sentiment.

Table II comparison table with existing methods

Method	Uses Text	Uses Image	Uses Video	Personalized
Collaborative Filtering	Yes	No	No	Yes
CNN	Partial	Yes	Partial	No
Proposed Method	Yes	Yes	Yes	Yes

7. CONCLUSION AND FUTURE SCOPE

This paper has presented an end-to-end framework for an AI-based automatic music recommendation system built specifically for WhatsApp Status. By combining the complementary strengths of Vision-Language Models for scene understanding with Large Language Models for semantic reasoning, the system automates the otherwise complex task of pairing audio with visuals. The experimental results validate the system's ability to generate contextually relevant, emotion-aware music suggestions without compromising user privacy or requiring historical usage data.

The contributions of this work are threefold: (1) the design of a privacy-centric, stateless recommendation architecture; (2) the novel application of Moondream 2 and Gemini for cross-modal translation from pixels to music tags; and (3) a demonstration of how multimodal AI can reduce decision fatigue in social media content creation.

Future research will focus on reducing system latency through the quantization of models for on-device deployment (Edge AI), thereby removing the dependency on cloud APIs. Additionally, we aim to integrate audio analysis to process ambient sound and speech within the video, creating a truly tri-modal (Visual-Audio-Text) understanding system. Finally, while the current system is stateless, an optional 'personalization layer' could be explored, allowing users to fine-tune recommendations based on their preferred genres while maintaining data sovereignty.

8. CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this paper. This research was carried out solely for academic purposes and carries no commercial affiliation with Spotify, Google, or Meta Platforms (WhatsApp).

9. DATA ACCESS STATEMENT

Readers seeking the code and architectural diagrams behind this study's findings may contact the corresponding author, who will provide them upon reasonable request. No user data was stored or retained during the experimental phase of this project.

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