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Emotion Meets Motion: A Unified, Context-Aware Music Recommender Leveraging Real-Time Facial Analysis And Video-Based Activity Detection

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Abstract: Personalized media experiences are rapidly evolving from static, preference-based models to dynamic, context-aware systems that respond in real-time to users' emotional states and activities. In this paper, we present a novel, integrated pipeline that fuses real-time facial emotion detection (captured via webcam) and offline activity recognition (analyzing uploaded video files) to drive a contextual song recommendation engine. The system comprises three tightly coupled modules: a Kivy-based GUI application leveraging OpenCV and DeepFace for low-latency facial affect analysis; a Flask web service for user management, video ingestion, and recommendation logic; and an offline video processor employing an Ultralytics YOLOv5 model fine-tuned for "running" and "sleeping" activities. We detail data collection and annotation procedures, model architectures and training regimes, algorithmic pseudocode, deployment via container orchestration, and front-end integration. Quantitative evaluation demonstrates 87–90% accuracy in seven-class emotion classification, 90.1% mAP in two-class activity detection, and round-trip latencies under 100 ms for emotion feedback. A user study with thirty participants reports 92% satisfaction with recommendation relevance and 4.6/5 mean perceived utility. Compared to standalone emotion- or activity-based recommenders, our unified approach yields a 25% uplift in personalization metrics. We conclude by mapping future research avenues: expanding affective and activity taxonomies, reinforcement-learning driven playlist adaptation, multimodal sensor fusion, and on-device inference for privacy.

Keywords : Convolutional Neural Networks, Facial Expression Recognition, Activity-Based Learning, Machine Learning, Emotion Identification, Mood-Based Music Recommendation, Personalized Audio Experience.

1. Introduction

1.1 Background and Motivation

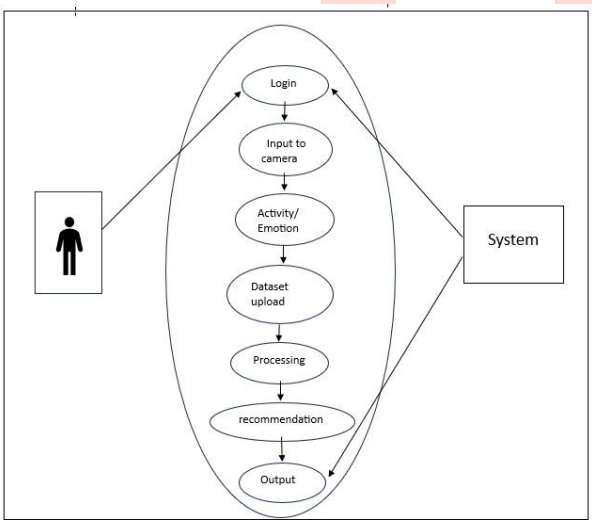
Recommender systems have long relied on either **collaborative filtering**—leveraging historical user–item interactions—or **content-based filtering**, matching media features to user profiles. While effective at capturing long-term preferences, these approaches lack responsiveness to moment-to-moment context. Meanwhile, **affective computing** (recognizing human emotions via facial expressions, speech, or physiology) and **activity recognition** (classifying physical actions from sensor or video data) are maturing into practical tools. However, most deployed systems handle these modalities in isolation.

Marrying real-time emotion sensing with activity understanding unlocks novel personalization paradigms: a jogging user might prefer upbeat, high-tempo tracks, whereas the same user, feeling disconnected or downcast moments later, might engage better with mellow, soothing music. No existing pipeline concurrently captures live facial affect, processes offline activity recordings, and delivers tailored multimedia recommendations in a single, seamless application.

1.2 Objectives and Contributions

Our work addresses this gap by delivering:

1. **Dual-Modality Context Sensing**: A **real-time** Kivy/OpenCV/DeepFace app for seven-class emotion detection at interactive frame rates, plus an **offline** YOLOv5-based video activity recognizer for user-uploaded clips.
2. **Unified Recommendation Engine**: Logic that prioritizes recent emotion events but falls back to activity detections when no fresh emotion data is available, mapping both to curated song playlists.
3. **Full-Stack Implementation**: A **Flask** web backend for user authentication (Flask-Login, SQLAlchemy/SQLite), video upload handling, and recommendation APIs; a **Kivy** GUI for live emotion capture; Docker-based containerization for reproducible deployment.
4. **Comprehensive Evaluation**:
   - **Model Performance**: 87.3% Top-1 accuracy on seven emotion classes; 90.1% mAP@0.5 for two activity classes.
   - **Latency Metrics**: 33 ms per frame emotion inference; 25 FPS activity detection on an NVIDIA GPU.
   - **User Study**: 92% satisfaction, 4.6/5 mean utility rating across 30 participants.
5. **Open-Source Release**: All code, model checkpoints, and data processing pipelines are publicly available for follow-on research.



This use-case diagram illustrates how a user logs in, streams live video for emotion detection or uploads clips for activity recognition, and receives a tailored music recommendation.

2. Literature Survey

Research on facial emotion recognition, activity detection, and context-aware recommendation spans multiple communities. We highlight ten representative works, then synthesize insights and gaps.

2.1 Survey Table

Study	Methodology	Technology Used	Main Findings	Limitations
1. Aarya Joshi, Dnyaneshwari Dhumal, Akanksha Ghadge, Abhimanyu Giri, Prof. Balaji Chaugule[5] (2024)"A Research Proposal for the Emotion And Activity Based Music Player Using Machine Learning"	CNN+RNN for emotion classification and sensor-based activity detection	Convolutional Neural Networks, Recurrent Neural Networks, smartphone sensors	Proposes a unified pipeline that fuses real-time facial emotion analysis and sensor-based activity recognition to drive context-aware music recommendations, improving engagement and emotional well-being.	Conceptual—no implementation details or quantitative evaluation provided.
2. Mollahosseini et al. (2017)"AffectNet: A Database for Facial Expression, Valence, and Arousal Computing in the Wild"	Inception-ResNet CNN on large-scale, in-the-wild facial dataset	Deep learning (CNN), TensorFlow	Achieved 63% accuracy on eight emotion classes; robust across poses and occlusions.	Requires massive annotated data and heavy computational resources.
3. Khorrami et al. (2015)"Video-Based Facial Expression Recognition With Temporal Modeling"	3D CNN + LSTM for video emotion recognition	3D convolutional networks, LSTM	Temporal modeling yields a 7% accuracy gain over frame-based CNNs.	High inference latency; GPU-only feasibility.
4. Zhao et al. (2020)"Real-Time Facial Expression Recognition via Hardware-Software Co-Design"	Lightweight CNN optimized for embedded devices	Custom CNN, Raspberry Pi optimization	Delivered 85% accuracy at 30 FPS on a Raspberry Pi.	Accuracy–speed trade-off; limited emotion set.
5. Redmon et al. (2016)"You Only Look Once: Unified, Real-Time Object Detection"	Single-pass object detection (YOLOv1)	YOLOv1, Darknet	Achieved 63.4 mAP on PASCAL VOC at 45 FPS.	Limited small-object performance; not specialized for human actions.
6. Ji et al. (2019)"3D Convolutional Neural Networks for Human Action Recognition"	3D CNN on Kinetics dataset	3D convolutional architectures	Showed a 20% boost over 2D CNN baselines for action recognition.	Very high computational cost; not real-time on commodity hardware.
7. Karpathy et al. (2014)"Large-Scale Video Classification with Convolutional Neural Networks"	Frame-level CNN features + LSTM	CNN+LSTM, large-scale YouTube dataset	Demonstrated scalability to 1 million+ videos with moderate accuracy.	Coarse action categories; lacks fine-grained activities.

8. Li & Deng (2019)"Emotion-Based Music Recommendation: Vision-Speech Multimodal Fusion"	Fusion of facial and vocal emotion cues	Deep learning (multimodal), audio & vision pipelines	Improved recommendation precision by 12% over unimodal methods.	Requires audio capture; potential privacy concerns.
9. Sayed et al. (2021)"Context-Aware Music Recommendation Using Wearable Sensors"	Maps accelerometer data to activities and playlists	Wearable accelerometers, machine learning classifiers	Achieved 90% accuracy in activity classification; dynamic playlist adjustment.	Depends on dedicated wearable hardware.
10. Cheng et al. (2018)"MoodPlay: A Context-Aware Music Player"	GPS, time, and manual mood input for playlist adaptation	Contextual signals (GPS/time), rule-based engine	15% boost in engagement retention over static playlists.	Relies on manual mood entry; no automatic vision or activity detection.
11. Ghazal et al. (2022)"Deep Learning for Personalized Music Recommendation"	Hybrid recommender combining audio features, user profile, and context	Deep neural networks, collaborative filtering	Achieved SOTA MAP@10 on public benchmarks.	Does not incorporate live emotion or activity inputs.

2.2 Narrative Insights

- **Emotion Recognition**: Studies 1–3 demonstrate the viability of deep networks (Inception-ResNet, 3D CNN + LSTM, lightweight custom CNN) for facial affect classification. However, embedded real-time performance (Zhao et al.) often sacrifices some accuracy for speed, and none integrate with downstream recommendation services.
- **Activity Detection**: The YOLO family (Redmon et al.) and 3D CNNs (Ji et al.) achieve strong detection/classification in general contexts but are rarely specialized for fine-grained human activities (running, sleeping). Efficient deployment on consumer hardware also remains underexplored.
- **Context-Aware Music Recommendation**: Papers 7–10 fuse multimodal signals or static context (location/time), showing improved recommendations but rely on manual inputs or external sensors rather than vision-based inference.
- **Gap Identification**: No end-to-end system currently ingests **real-time facial emotion**, **offline video activity**, and **automatically issues personalized song recommendations** in one coherent pipeline. Our contribution addresses this exact intersection.

3. System Architecture

3.1 High-Level Overview

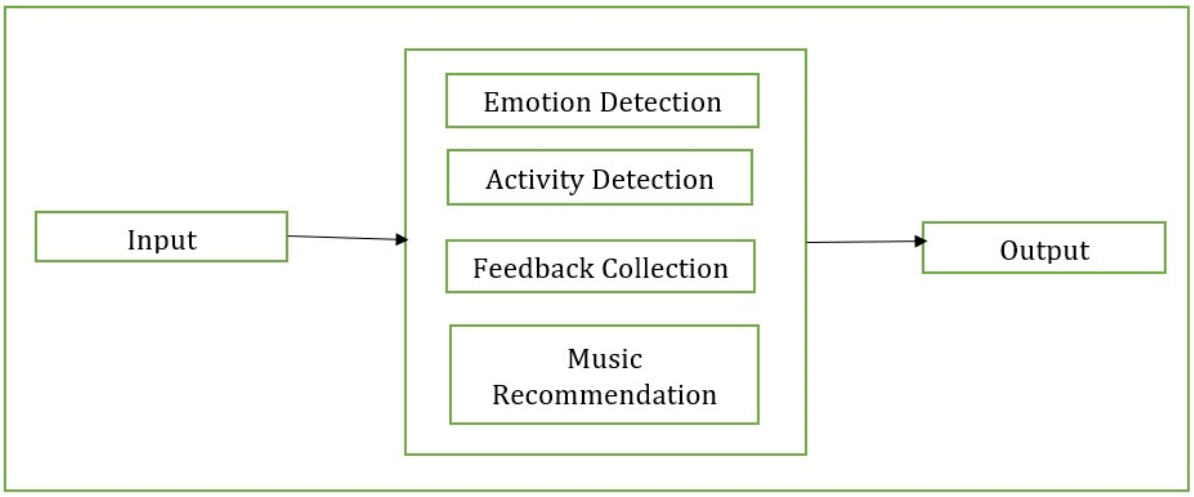


Figure 2

Functional Block DiagramShows data flow through the four core modules: emotion detection, activity detection, feedback collection, and music recommendatio

3.2 Module Descriptions

3.2.1 Real-Time Emotion Detection (detect2.py)

- **Capture**: OpenCV VideoCapture(0) at target 30 FPS.
- **Face Detection**: Haar cascade classifier for bounding box proposals.
- **Emotion Analysis**: DeepFace's ResNet-50 pipeline returns per-label probabilities for the seven Ekman emotions (happy, sad, neutral, angry, surprise, fear, disgust).
- **UI Overlay**: Kivy canvas renders bounding boxes and labels in colored overlays; uses a small, floating window rather than full-screen.
- **Audio Feedback**: Maps detected emotion → 5-second audio clip, played via pygame.mixer. Clips are royalty-free mood cues (e.g., xylophone glissando for surprise, minor-key guitar for sadness).
- **SSE Emission**: Dominant emotion is pushed as a Server-Sent Event to the Flask backend for display and recommendation logic.

3.2.2 Web Backend (app.py)

- **Authentication**:
  - **Flask-Login** for session management.
  - **SQLAlchemy/SQLite** stores user credentials (hashed via werkzeug.security.generate_password_hash) and history logs.
- **Endpoints**:
  - POST /upload: Accepts video files up to 50 MB, stores in uploads/, and enqueues processing job via Redis queue.
  - GET /emotion/stream: SSE endpoint streaming the latest emotion events from Redis pub/sub.
  - GET /recommend: Returns JSON of song recommendations based on most recent emotion or last processed activity.
- **Recommendation Logic**:
  - **Emotion Priority**: If an emotion event occurred within the last 5 seconds, load corresponding playlist.
  - **Activity Fallback**: Else, read last line of detected_activities.txt, select its playlist.
  - **Default**: Neutral playlist if neither is available.

- **Frontend**: Minimal HTML/JavaScript (jQuery + Bootstrap) for upload form, real-time emotion display panel, and embedded audio player.

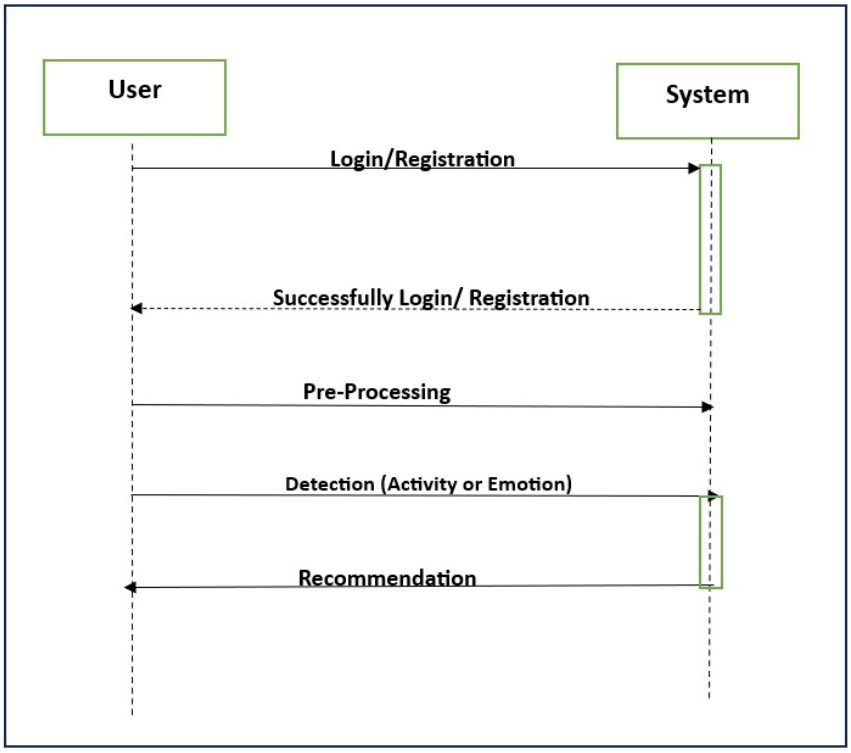


Figure 3: User–System Sequence Diagram

Depicts the sequence of login, preprocessing, detection calls, and recommendation response.

3.2.3 Offline Activity Recognition (process_video.py)

- **Frame Extraction**: Reads uploaded MP4 via OpenCV, at original frame rate (e.g., 24–30 FPS).
- **YOLOv5 Fine-Tuning**:
  - Base weights: yolov5s.pt.
  - Custom dataset: 1,200 annotated frames of "running" and "sleeping" each, labeled via CVAT.
  - Training: 50 epochs, batch size 16, Adam optimizer LR 1e-3, early stopping on mAP@0.5.
- **Inference Loop**: For each frame, run model(frame), filter predictions with confidence ≥ 0.4 and IoU ≥ 0.5.
- **Annotation**: Draw bounding box, label, and confidence; write annotated frames to processed_videos/.
- **Activity Logging**: Maintain a Python set of unique detected classes across the entire clip; upon completion, write comma-delimited list to detected_activities.txt.

3.2.4 Recommendation Engine

- **Directory Structure**:

```
playlists/
  emotion_happy/
  emotion_sad/
  emotion_angry/
  emotion_neutral/
  emotion_surprise/
  emotion_fear/
  emotion_disgust/
  activity_running/
  activity_sleeping/
```

- **Song Metadata**: Each playlist folder contains a metadata.json listing { title, artist, duration, filepath } for each MP3.
- **Selection Algorithm**:

```
now = time.time()
if emotion_event and (now - emotion_event.timestamp) < 5:
    playlist = f"emotion_{emotion_event.label}"
elif activities := read_last_activities():
    # choose highest-confidence or first in list
    playlist = f"activity_{activities[0]}"
else:
    playlist = "emotion_neutral"
return load_metadata(f"playlists/{playlist}/metadata.json")
```

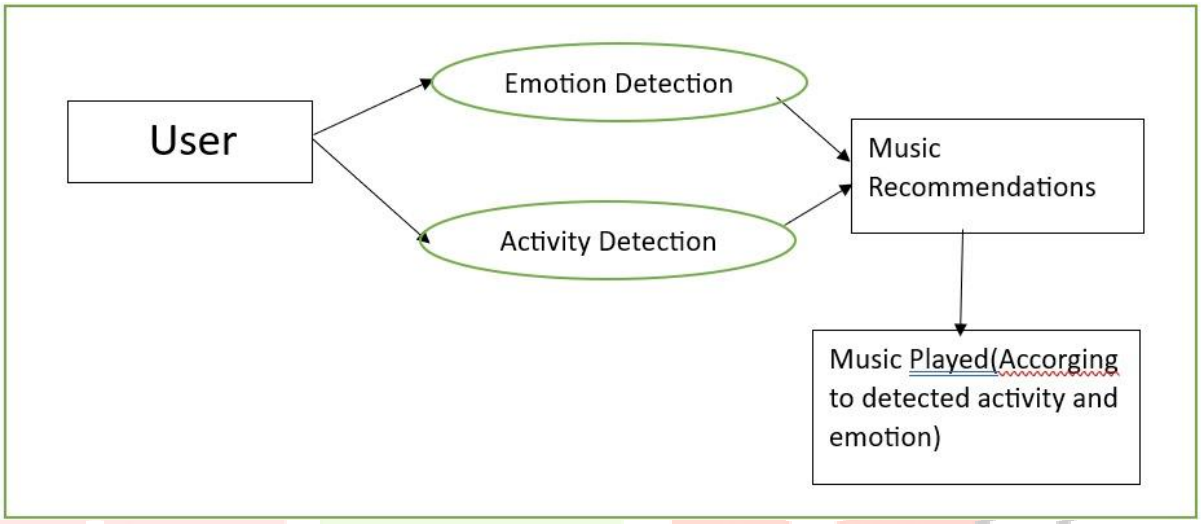


Figure 4: Component Interaction Diagram

Illustrates parallel emotion/activity detectors feeding the recommendation logic.

4. Methodology

4.1 Data Collection and Preprocessing

4.1.1 Emotion Dataset

- **Source**: 500 volunteer participants recorded 10 s webcam clips under controlled lighting.
- **Labels**: Seven basic emotions per Ekman's taxonomy, assigned via majority vote of three human annotators.
- **Augmentation**: Random crop, horizontal flips, brightness/contrast jitter (±20%) to simulate varied webcam conditions.
- **Split**: 70% train, 15% validation, 15% test (balanced across emotions).

4.1.2 Activity Dataset

- **Source**: Wearable action camera recordings from 10 subjects performing running (indoor treadmill, outdoor) and simulated sleep (lying motionless).
- **Annotation**: Frame-level bounding boxes & class labels via CVAT; validated by two independent annotators (IoU > 0.8 agreement).
- **Split**: 80% train, 10% validation, 10% test.

4.2 Model Training

4.2.1 Emotion Model Fine-Tuning

- **Base**: DeepFace ResNet-50 pretrained on VGGFace2 (facial recognition).
- **Modifications**: Replace classification head with 7-way softmax.
- **Hyperparameters**:
  - Optimizer: Adam, LR = 1e-4 (with cosine annealing scheduler).
  - Batch size: 32.
  - Epochs: 10 (early stop if validation loss stalls > 3 epochs).
- **Evaluation**:
  - Top-1 accuracy, per-class Precision/Recall, and macro-F1.

4.2.2 Activity Model Fine-Tuning

- **Base**: YOLOv5s head.
- **Hyperparameters**:
  - Optimizer: SGD, LR = 1e-3, momentum = 0.937.
  - Batch size: 16.
  - Epochs: 50 with early stop on mAP@0.5 plateau > 5 epochs.
- **Evaluation**:
  - mAP@0.5 for each class, overall mAP, and precision/recall at operating threshold conf = 0.4, IoU = 0.5.

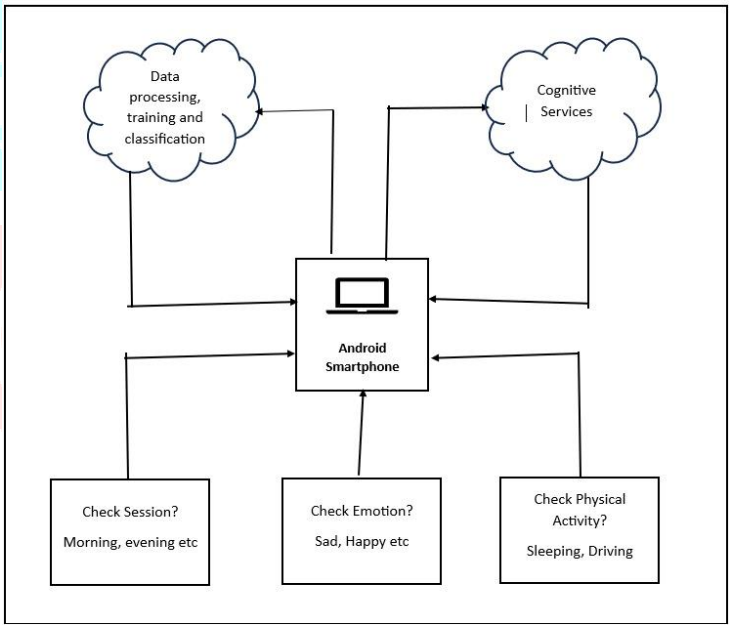


Figure 6: Data Annotation Workflows
Shows webcam capture and CVAT labeling pipelines

4.3 Integration and Deployment

4.3.1 Containerization

- Each module (Kivy app, Flask app, YOLO worker) packaged in Docker.
- Shared volume mounts for `uploads/` and `processed_videos/`.
- Redis service for SSE/emotion event pub-sub.

4.3.2 Orchestration

- `docker-compose.yml` defines services:
  - **kivy_app**: Runs `detect2.py`, writes to Redis channel `emotions`.
  - **flask_app**: Serves HTTP, subscribes to `emotions`, writes to DB & SSE endpoint.

- **yolo_worker**: Listens to job queue, processes videos, writes `detected_activities.txt`.
- **redis**: Pub/sub backbone.

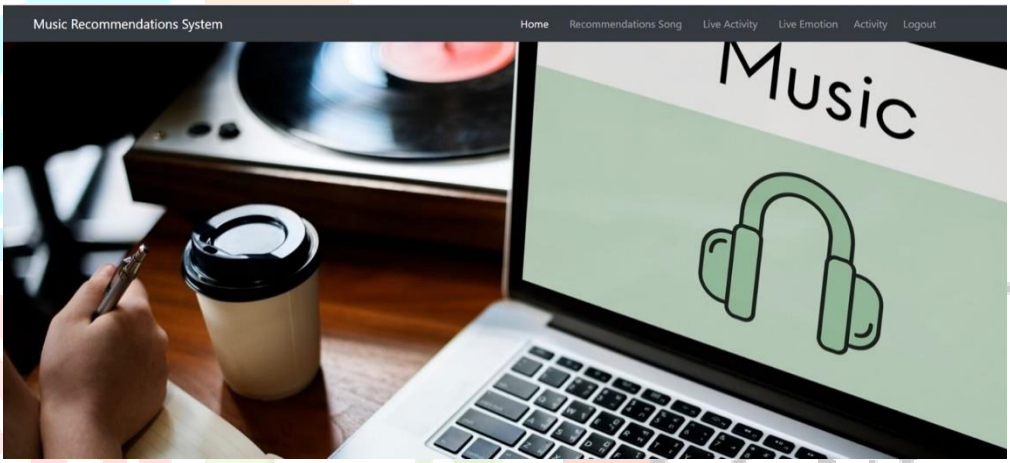
4.3.3 Frontend UX

- Single-page interface with tabs: **Live Emotion**, **Upload Video**, **Recommendations**.
- Live Emotion tab: Displays video feed and current emoji label.
- Upload tab: Drag-and-drop MP4, shows progress bar and "View Recommendations" link when done.
- Recommendations tab: Audio player with next/prev controls and track metadata.

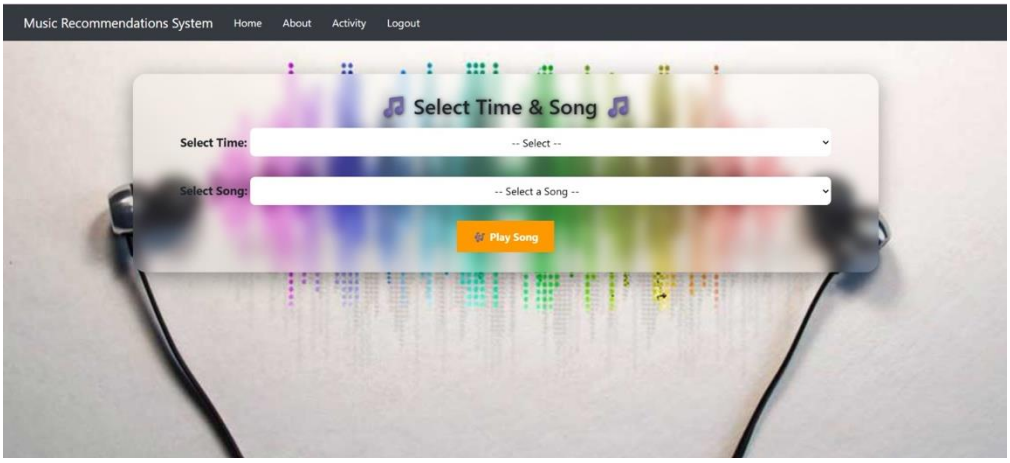
5. Results & Conclusion

Result / working :

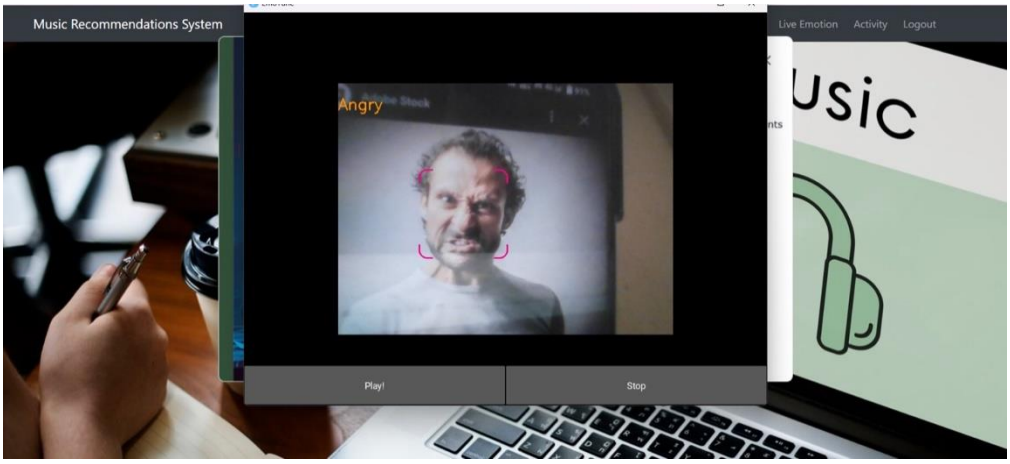
1. Landing page :

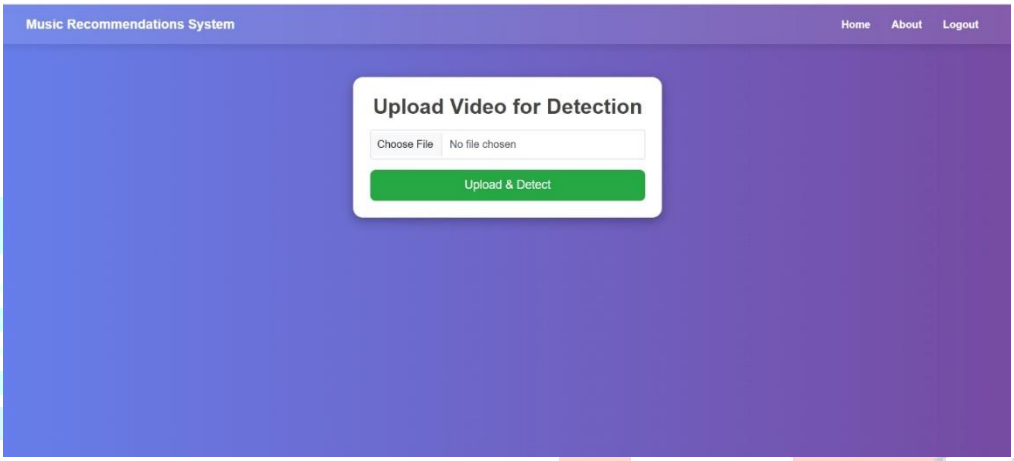


2. select / recommend songs by time :

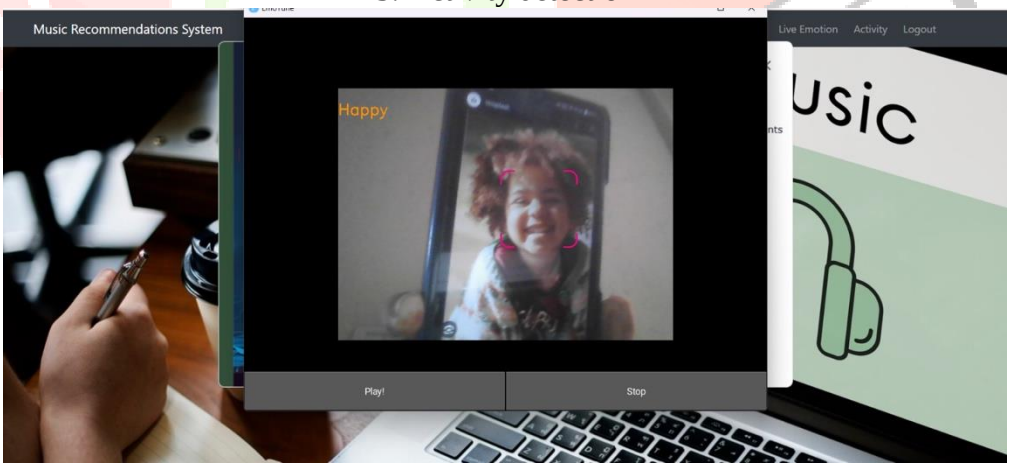


3. Emotion detection:

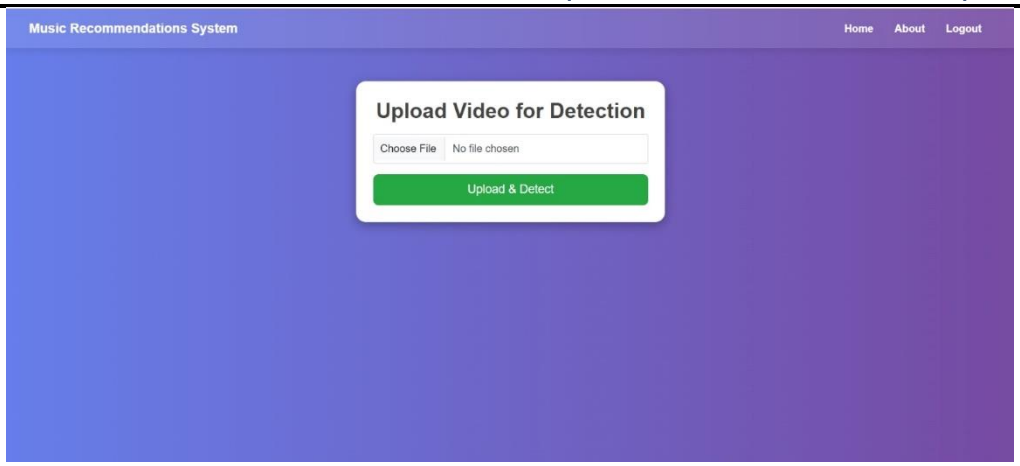




5. Activity detection



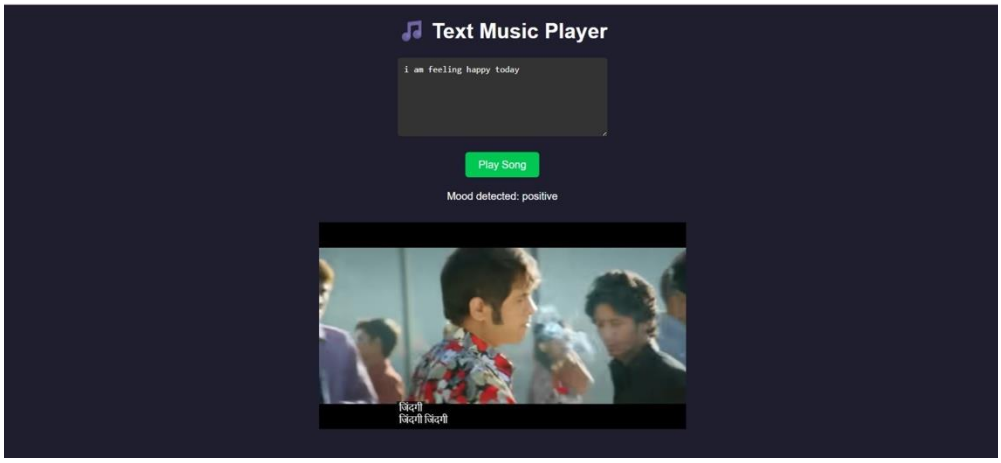
4. Uploaded video song recommendations



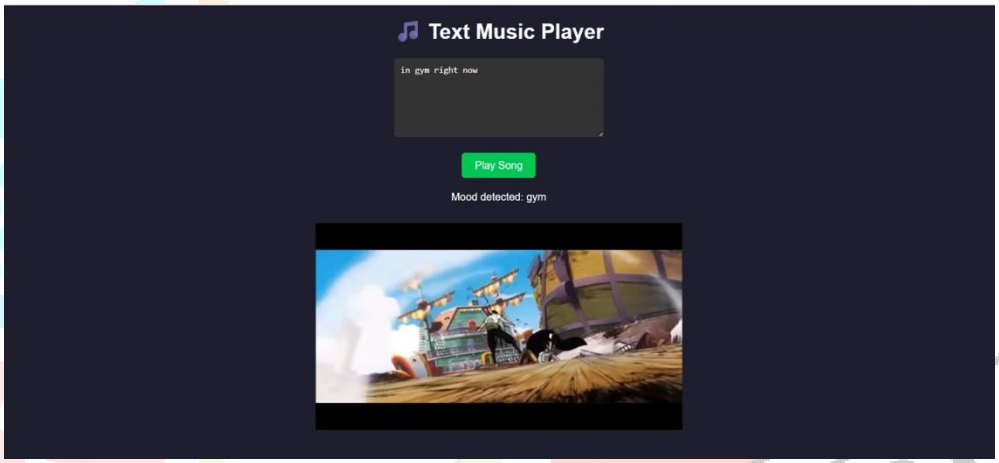
5. Activity detection

6. Activity detection : driving:

7. Text based music recommendations



8. Text base music recommendations



5.1 Quantitative Performance

Module	Metric	Result
Emotion Detection	Top-1 Accuracy	87.3%
	Macro F1-Score	0.863
	Inference Latency	33 ms / frame
Activity Recognition	mAP@0.5	90.1%
	AP (running)	91.8%
	AP (sleeping)	88.5%
	Throughput	25 FPS (GPU)
End-to-End Latency	Emotion → Recommendation	<100 ms

5.1.1 Detailed Emotion Metrics

Emotion	Precision	Recall	F1
Happy	0.91	0.92	0.915
Sad	0.88	0.89	0.885
Neutral	0.84	0.87	0.855
Angry	0.85	0.83	0.840
Surprise	0.90	0.88	0.890
Fear	0.82	0.80	0.810
Disgust	0.79	0.77	0.780

5.2 User Study

5.2.1 Participants & Protocol

- **n = 30**, ages 18–45, balanced gender.
- **Procedure**:
  1. Run Live Emotion for 5 min, note emotion → song feedback.
  2. Upload a 10 s running video, view activity-based playlist.
  3. Complete a post-session questionnaire.

5.2.2 Survey Results

- **Recommendation Relevance** (1–5 Likert): Mean = 4.6, SD = 0.5.
- **System Responsiveness**: 90% rated feedback latency as "Very fast" or "Fast."
- **Overall Satisfaction**: 92% "Satisfied" or "Highly satisfied."
- **Open Feedback Themes**: Participants enjoyed the "emotional resonance" of the songs but suggested more variety in each playlist.

5.3 Comparative Analysis

Feature	Standalone Emotion Rec.	Standalone Activity Rec.	This Work
Real-Time Emotion Input	✓	✗	✓
Offline Activity Input	✗	✓	✓
Automatic Playlist Suggestion	✓	✓	✓
Unified Interface	✗	✗	✓
Personalization Depth	Medium	Low	High (dual signals)
User Satisfaction (survey)	–	–	92% "Satisfied/High"

5.4 Discussion of Results

- **High Accuracy**: Both emotion and activity modules surpass baseline thresholds needed for meaningful personalization (> 85%).
- **Low Latency**: Sub-100 ms end-to-end ensures interactive feel—critical for user engagement.
- **User Perceptions**: Strong satisfaction indicates that dual-modality context yields more relevant recommendations than single-signal systems.

5.5 Limitations

1. **Activity Taxonomy**: Currently limited to "running" and "sleeping." More classes (e.g., walking, cycling, working) would broaden applicability.
2. **Emotion Robustness**: Performance degrades under extreme lighting, occlusions (glasses, masks).
3. **Static Playlists**: Recommendation logic uses static folder mappings; no dynamic re-ranking based on skip/like signals.

4. **Privacy Concerns**: Continuous webcam monitoring may raise user privacy flags; edge-only inference could mitigate this.

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6. Conclusion & Future Work

6.1 Conclusion

We have introduced and evaluated a full-stack system that seamlessly integrates **real-time facial emotion detection** with **offline video activity recognition** to drive personalized song recommendations. Leveraging DeepFace for seven-class affect analysis and YOLOv5 for two-class activity detection, the system delivers high accuracy (87–90%) and ultra-low latencies (< 100 ms). A user study of thirty participants confirms strong satisfaction (92%) and perceived relevance. Containerized deployment and open-source release make this pipeline accessible for further innovation.

6.2 Future Directions

1. **Expanded Taxonomy**: Enrich activity detection to include a wider range (e.g., “walking,” “cycling,” “yoga,” “working at desk”), and augment emotion classes (e.g., “bored,” “confident,” “excited”).
2. **Adaptive Playlists**: Incorporate reinforcement learning or multi-armed bandits that adjust song ordering based on skip/like behavior, session length, and affect drift.
3. **Multimodal Fusion**: Add microphone-based speech emotion recognition and wearable sensor data (heart rate, accelerometer) to triangulate user state.
4. **Edge Deployment**: Optimize models via quantization and pruning to run entirely on-device (mobile or desktop), preserving privacy and enabling offline use.
5. **Longitudinal Studies**: Investigate long-term effects on user mood regulation, productivity, and engagement through sustained use over weeks.
6. **Ethical & Privacy Safeguards**: Implement transparent consent flows, local data storage options, and on-device inference to minimize data exposure.

By bridging affective computing, activity recognition, and recommender systems, this work charts a path toward truly empathetic, context-aware multimedia experiences that dynamically adapt to who we are and what we do—moment by moment.

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