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VibeScreen: A Mood-Based Movie and Music Recommendation Mobile Application

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Abstract
The advancement of digital technology has driven the emergence of various innovations in delivering personalized entertainment content. One promising approach is a mood-based recommendation system, which enables users to receive suggestions for movies or music that match their emotional state. This study designed and developed VibeScreen, a prototype application for recommending movies and music based on user mood using sentiment analysis of text inputs. The system applies Natural Language Processing (NLP) techniques to classify user sentiment, which is then used to generate relevant entertainment recommendations. The application was developed using Flutter for the mobile interface and Flask for the backend services, with Firebase supporting user authentication and data storage. The dataset was collected through online questionnaires and secondary sources such as IMDb and Spotify. Testing results show that the system can provide mood-relevant recommendations with an interactive and responsive interface. This research contributes by integrating movies and music recommendations in a single platform, offering a more adaptive and emotionally relevant entertainment experience.

1. Introduction

The development of information and communication technology through digital media has brought significant changes to human life, especially in entertainment. Digitalization enables people to easily access films and music via streaming platforms and social media [1]. However, the abundance of choices often makes it difficult for users to select entertainment that matches their mood. Social media also plays an important role in shaping new preferences and habits in consuming entertainment. Mood is a crucial factor that influences a person's entertainment preferences . When feeling sad, individuals may prefer drama films or calming music, while in a happy state, they might be more inclined toward comedy films or fast-tempo music. Therefore, a recommendation system is needed to understand users' moods and help them choose suitable entertainment[2].

One possible approach is Sentiment Analysis, an NLP technique [3], that analyzes text to identify emotions or sentiments[4]. By applying this algorithm, the system can recognize users' moods from text inputs such as social media statuses or messages, and provide personalized film and music recommendations, making the selection process more efficient and enhancing the user experience[5]. Previous recommendation systems such as Spotify and Netflix mainly rely on *content-based filtering* and *collaborative filtering* methods that consider user history, genres, or ratings, but do not directly account for emotional or momentary mood states. Similarly,

mood-oriented applications (e.g., music-only mood recommenders) frequently target a single media domain and often use unimodal signals (e.g., audio features or facial/speech emotion cues), limiting their applicability across multimedia platforms. Recent studies in music and multimedia recommendation emphasize emotion-aware designs and real-time emotional context modeling, yet most proposed solutions either remain domain-specific or rely on handcrafted affective features rather than robust text-based emotion models[6].

Recent advancements in deep learning and pretrained language models, such as BERT and its Indonesian adaptation IndoBERT, have further improved sentiment classification accuracy by capturing contextual nuances in language. Incorporating these models into a mood-based recommendation system enables more reliable mood detection and better alignment between user emotions and suggested media content. As a result, such systems not only assist users in discovering entertainment that resonates with their current emotional state but also contribute to emotional wellbeing by offering content that can uplift or balance their mood[7].

However, most existing systems still face several unresolved challenges, such as the lack of bilingual mood understanding (English–Indonesian), the absence of integrated cross-media recommendation platforms combining movies and music, and limited contextual adaptation to Indonesian users' linguistic and cultural nuances. These limitations highlight the need for a more comprehensive and localized mood-based recommendationframework.

Therefore, this study aims to develop VibeScreen, a bilingual mood-based movie and music recommendation system that integrates IndoBERT for sentiment analysis to enhance emotional understanding, personalization, and contextual relevance for Indonesian users. The main contributions of this study include:

(1) implementing IndoBERT-based sentiment analysis for mood recognition in entertainment recommendation,
(2) integrating film and music recommendations within a single mobile platform, and
(3) providing a context-aware entertainment experience aligned with users' emotional states.

Compared with previous studies, the proposed VibeScreen model offers several advancements in terms of algorithm, data, domain, and performance. In terms of algorithm, VibeScreen utilizes the IndoBERT model for sentiment analysis, which captures contextual nuances of the Indonesian language more effectively than traditional classifiers such as SVM or Naïve Bayes. Regarding data, this study employs a bilingual and locally curated dataset of 56 movies and 64 music tracks tailored to Indonesian users' emotional context. In terms of domain, unlike existing emotion-aware systems that focus on a single medium (e.g., music-only recommenders), VibeScreen integrates both film and music recommendations within a unified platform. Finally, in terms of performance, IndoBERT achieved 91.2% accuracy and an F1-score of 0.89, outperforming the baseline SVM (83.5%) and Naïve Bayes (78.9%) classifiers. These results demonstrate that VibeScreen provides more reliable mood detection and a broader, contextually adaptive recommendation experience compared to previous approaches[8].

2. Research Method

The VibeScreen application was developed using the Waterfall method. which provides a structured and sequential approach to system development, ensuring that each stage is completed before proceeding to the next. The stages applied in this study include Requirements, System Design, Implementation, Testing, and Maintenance. Although Agile and Prototyping methods are often used in mobile application development, the Waterfall model was selected because it offers a clear and well-documented process suitable for academic research with fixed requirements, ensuring consistency and effective evaluation of the IndoBERT-based sentiment analysis across all development phases., and Maintenance, as shown in (Figure 1)

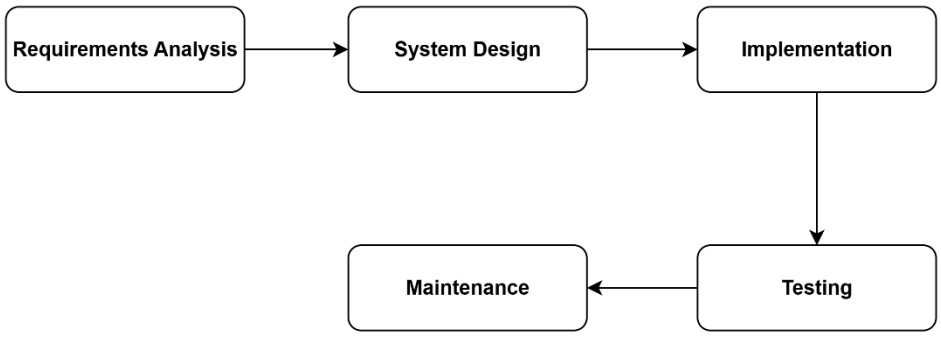

Figure 1. Waterfall Method

a. Requirements Analysis

At this stage, the researchers conducted observations and literature studies to identify user needs related to film and music recommendations based on user mood. The requirement analysis resulted in a list of functional features such as mood-based recommendation, search, favorite storage, and review.

b. System Design

The system design was modeled using UML diagrams to illustrate workflows, user interactions, and database structures. The VibeScreen system consists of four main components: the frontend (Flutter), backend (Flask), sentiment analysis module (IndoBERT), and databases (MySQL and Firebase Firestore). These components interact to generate mood-based movie and music recommendations.

The Flutter frontend supports both mobile and web platforms, handling user authentication, mood input, recommendation display, and favorite management. User mood input is sent via HTTPS to the Flask backend through RESTful APIs. The backend functions as the central processing unit, connecting the interface, NLP module, and databases, and managing endpoints such as login, register, analyze mood, recommendations, favorites, and reviews. User-related data is stored in Firestore, while movie and music metadata is kept in MySQL.

Text preprocessing including tokenization, case folding, punctuation and stop-word removalprepares input before classification using the fine-tuned IndoBERT model. The model achieved 91.2% accuracy and 0.89 F1-score on a labeled Indonesian sentiment dataset, outperforming SVM and Naïve Bayes baselines.

The detected mood label is then used to retrieve relevant film and music data from MySQL, which is returned to the frontend as personalized results. Favorite and review interactions are synchronized with Firebase Firestore for real-time updates. Figure 2 illustrates the complete system architecture and data flow. (Figures 2) shows the system architecture diagram, which summarizes the data flow from mood input to recommendation generation, covering all communication processes between the frontend, backend, NLP module, and databases.

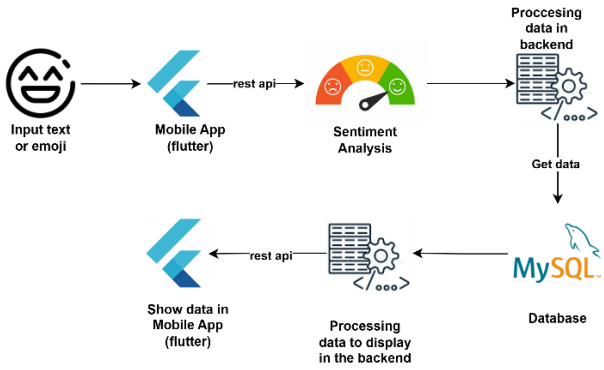

Figure 2. Architectural model

c. Implementation

In the implementation stage, the VibeScreen application was developed using a combination of technologies. The backend was built with Flask integrated with MySQL and Firebase Firestore, while sentiment analysis was performed using IndoBERT. For the frontend, the system supported both web and mobile versions using Flutter[9].

The dataset used in this study consisted of 56 movie entries and 64 music entries, which were collected through a Google Form survey. Participants were asked to recommend films and songs based on specific genres such as comedy, horror, or drama. The mood alignment (e.g., suitable for sad or happy moods) was manually determined by the researcher during dataset compilation, considering the emotional context typically associated with each genre. These data were stored in a MySQL database and linked to the recommendation system, allowing the application to generate film and music suggestions that correspond to the user's inputted mood.

d. Testing

The testing process applied Black Box Testing to verify whether each feature functioned according to the predefined requirements. Features tested include user authentication, mood-based recommendation, search, favorite management, and review submission.

e. Maintenance

The final stage focused on evaluation and improvements, including bug fixing, feature refinement, and the potential integration of additional functions such as notification systems and real-time updates.

3. Result and Discussions

Requirements Analysis

Requirement analysis identified key features including mood-based recommendations using IndoBERT, manual search, favorite storage, user reviews, and notification services to provide personalized entertainment experiences tailored to user emotional states.

The IndoBERT model achieved 91.2% accuracy and 0.89 F1-score, outperforming SVM (83.5%) and Naïve Bayes (78.9%), confirming its effectiveness in classifying positive, neutral, and negative moods for recommendation purposes. System responsiveness testing on a mid-range smartphone showed an average 1.8-second response time, indicating good real-time usability.

Most core features performed successfully during testing, except Facebook Login, which experienced authentication issues due to API permission restrictions between Facebook Developer Console and Firebase

Authentication. Future solutions include enhanced OAuth configuration or adopting Firebase Custom Authentication.Mood-based recommendation has been proven effective in enhancing user satisfaction and engagement in entertainment systems[10]. The integration of sentiment analysis into recommendation systems can improve the relevance and personalization level of the suggested content [11]. BERT-based models, such as IndoBERT, have shown strong performance in Indonesian sentiment classification due to their ability to capture contextual meanings and emotional nuances [12]. Furthermore, the application of sentiment-driven recommendations combined with interactive features such as favorites, reviews, and notifications can increase user retention and encourage continuous engagement with the platform [13]. Therefore, the implementation of these features in the VibeScreen application is intended not only to match entertainment content with users' moods but also to create a more dynamic, adaptive, and engaging experience [14].

System Design

The system design was carried out using Unified Modeling Language (UML) to illustrate workflows and user interactions. The Use Case Diagram describes the main interactions between users and the VibeScreen system. It outlines the primary activities such as logging in, entering mood input, viewing film and music recommendations, saving favorite items, and submitting reviews. This diagram helps define the scope of user roles and the corresponding system functionalities. (Figures 3) illustrate the Use Case Diagram.

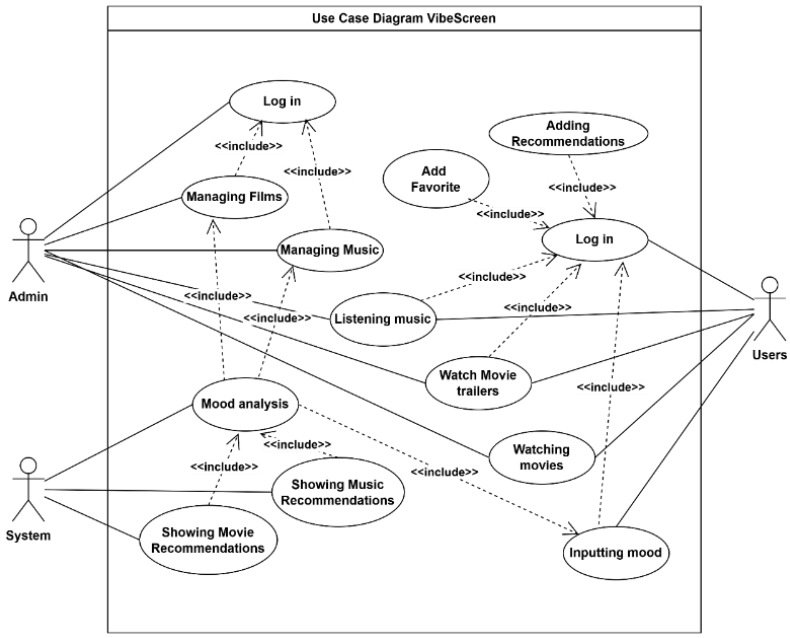

Figure 3. Use Case Diagram

The Activity Diagram illustrates the workflow of key processes within the VibeScreen application, including login, mood detection, recommendation generation, and data management. It visualizes how the system responds to user inputs and transitions between activities, providing a clear overview of logical sequences and process dependencies. (Figures 4) illustrate the Activity Diagram.

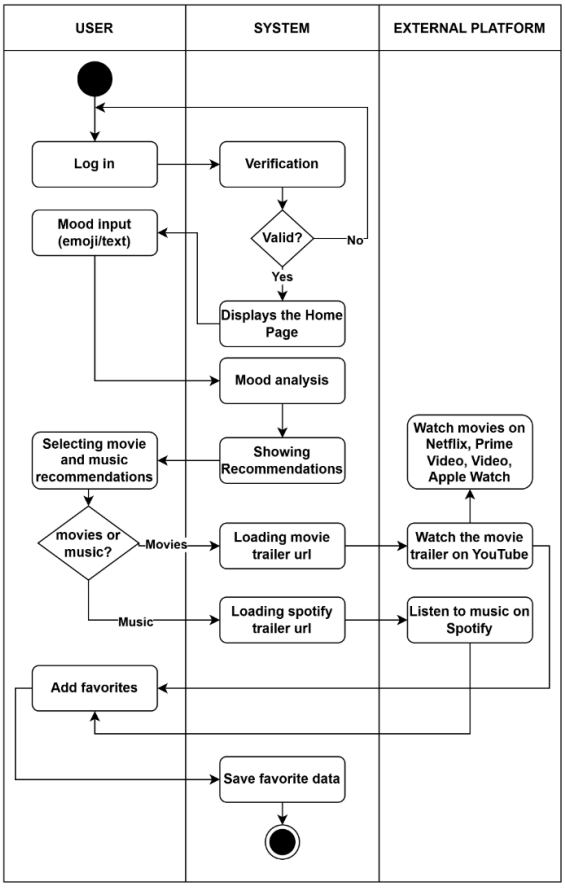

Figure 4. Activity Diagram

This Flowchart provides a general view of the system's operational flow, beginning from user mood input to sentiment analysis using the IndoBERT model, followed by recommendation generation, and finally the display of personalized film and music results. The flow demonstrates how data moves through the application, ensuring that each component functions cohesively. (Figures 5) illustrate the Flowchart.

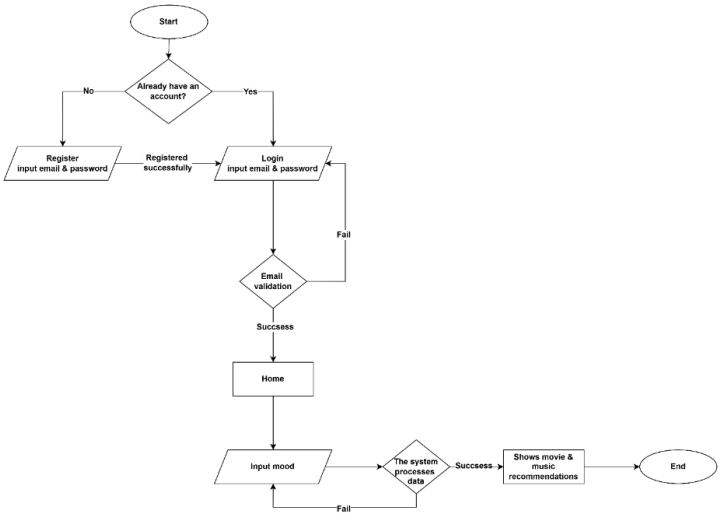

Figure 5. Flowchart

Furthermore, an Entity Relationship Diagram (ERD) was created to design the database structure, including entities such as Users, Films, Music, Favorites, and Reviews. The Users entity is linked to Favorites and Reviews, while Films and Music entities are connected to Favorites and Reviews through unique IDs. This design supports efficient data management between MySQL for film and music datasets and Firebase Firestore for user-related data, ensuring that interactions between users, system processes, and databases are well-organized and documented, facilitating the implementation phase of the VibeScreen application. (Figures 6) illustrate the Entity Relationship Diagram.

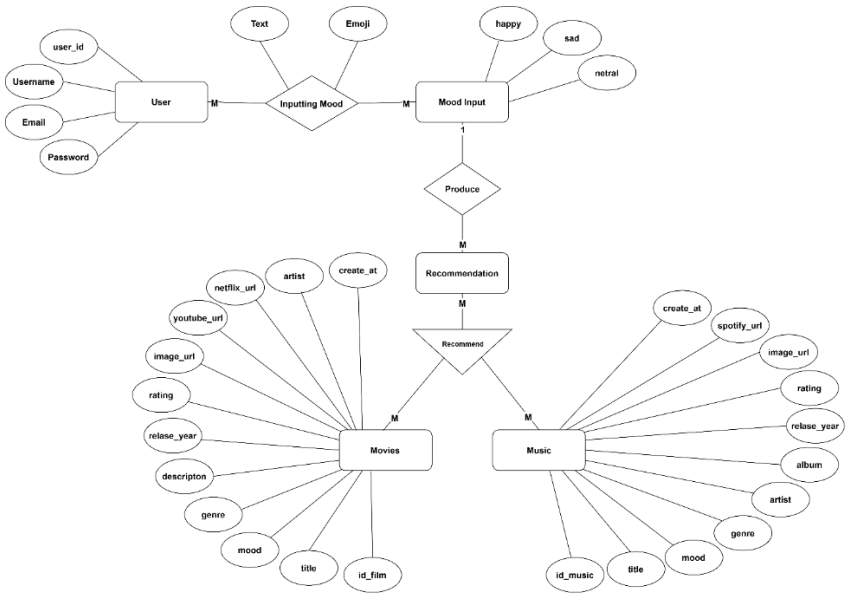

Figure 6. Entity Relationship Diagram

Implementation

The implementation of the VibeScreen application followed the system design by integrating frontend and backend components. The frontend was developed using Flutter to support both mobile and web platforms, implementing key features such as mood input, recommendation display, favorite management, and review submission with real-time data updates.

(Figures 7 and 8) illustrate the main user interface, including authentication screens (Login and Register) with support for email/password, Google, and Facebook Sign-In, as well as the Home and Mood-Based Recommendation screens. These interfaces demonstrate core functionalities, enabling users to input mood, view personalized movie and music recommendations, and interact smoothly with the system.

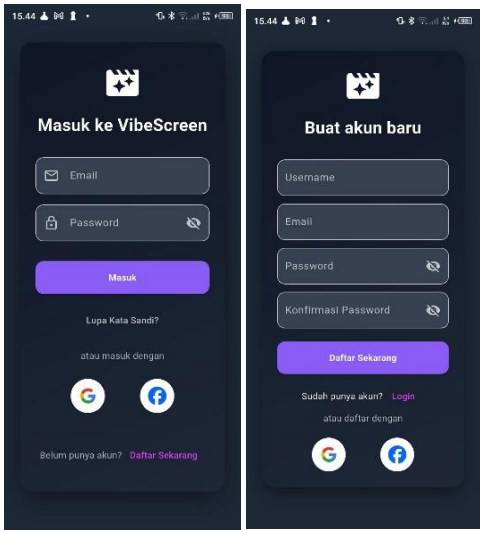

Figure 7. Login Screen and Register Screen

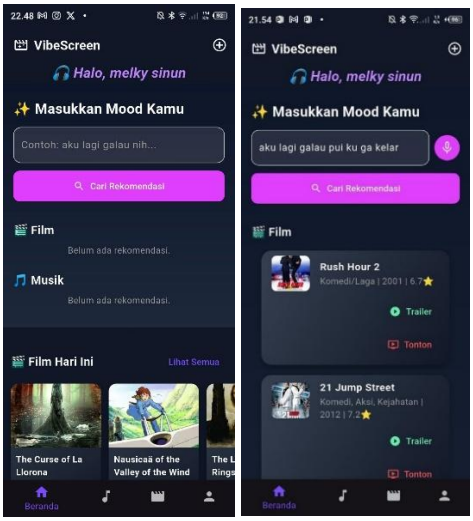

Figure 8. Home Screen and Recommendations Screen

(Figures 9 and 10) illustrate the main content interaction features of VibeScreen. The Music and Film screens enable users to browse available content, view essential details such as artist or genre, play tracks or trailers, and manage favorites. Meanwhile, the Favorite and Review screens allow users to access saved items, remove or view detailed content, and submit or read community reviews. These features support personalized exploration and enhance user engagement with the application.

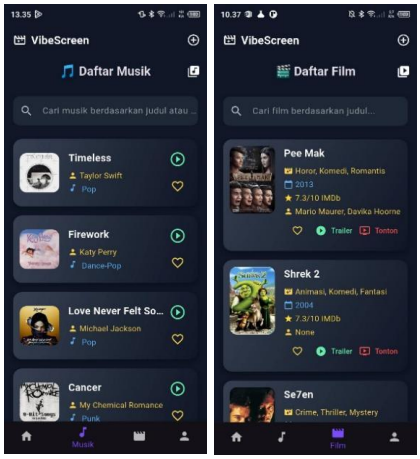

Figure 9. Musik Screen and Film Screen

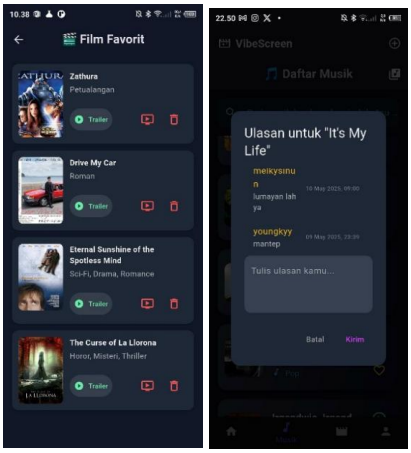

Figure 10. Favorite Screen and View reviews Screen

(Figures 11) show the Profile and Edit Profile screens of the VibeScreen application. The Profile screen displays user information such as display name, email, and profile picture, and provides access to features like viewing favorites and reviews. The Edit Profile screen allows users to update their personal information, including display name, password, and profile picture, ensuring their account remains current and secure. These screens demonstrate the user account management features of VibeScreen, giving users control over their personal data and enhancing the overall usability and personalization of the application.

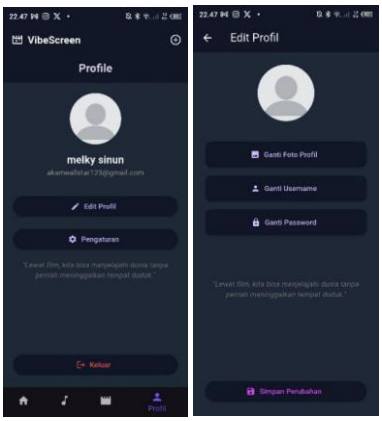

Figure 11. Profile Screen and Edit Profile Screen

Testing

Application testing was conducted using the Black Box Testing method to ensure that all features functioned according to the specified requirements. The testing results indicated that most features performed as expected, except for the Login with Facebook feature, which experienced an authentication issue due to API integration limitations. Overall, the VibeScreen application achieved a success rate of 91.7%, demonstrating reliable functionality across core components.

Table 1. Black Box Testing

No	Feature	Test Steps	Expected Result	Actual Result / Status
1	Login	Enter valid email/password, click login	User successfully navigates to Home screen	As expected / Pass
2	Login with Google	Click Google Sign-In button, select account	User successfully logs in using Google account	Not working / Fail
3	Login with Facebook	Click Facebook Sign-In button, login	User successfully logs in using Facebook account	As expected / Pass
4	Register	Enter new account data (email, password, display name), click register	New account is created and user navigates to Home screen	As expected / Pass
5	Mood Input	Enter mood text, click submit	System displays film & music recommendations according to mood	As expected / Pass
6	Film Recommendation	Select a recommended film	Film details are displayed; trailer can be opened	As expected / Pass
7	Music Recommendation	Select a recommended music track	Music details are displayed; track can be played	As expected / Pass
8	Favorites	Add film/music to favorites	Item appears in the Favorites screen	As expected / Pass
9	View Reviews	Open film/music detail	User reviews are displayed	As expected / Pass
10	Add Review	Enter comment and rating, click submit	Review is saved and displayed on screen	As expected / Pass
11	Profile	Open Profile screen	User data is displayed correctly	As expected / Pass
12	Edit Profile	Update display name, password, or photo, save changes	Changes are saved and reflected in Profile screen	As expected / Pass

Discussion

The implementation results indicate that the VibeScreen application can deliver real-time film and music recommendations according to user mood. The use of the IndoBERT model for sentiment analysis proved effective in classifying moods [15], [16]from user text input. Compared to previous studies that focused only on data management or static recommendations, VibeScreen introduces multi-platform integration and review features that allow greater user interaction. Another strength of the system is the dual-database integration (MySQL and Firestore), which supports flexible data synchronization. However, the limitation of this study lies in the relatively small dataset, which may affect the accuracy of recommendations. Future work may focus on expanding the dataset and applying advanced machine learning techniques such as collaborative filtering or hybrid approaches [17], [18]to enhance personalization and recommendation precision. Conclusions and Future Works

4. Conclusions and Future Works

This study successfully developed VibeScreen, a mood-based movie and music recommendation application integrating IndoBERT sentiment analysis, MySQL, and Firebase Firestore to deliver personalized recommendations, favorite management, reviews, and profile features. Testing results show that all core functionalities operated effectively, providing accurate mood-to-content alignment and a positive user experience.

In addition to entertainment, VibeScreen can also support emotional well-being by recommending content that matches users' moods and encouraging emotional awareness. Its sentiment-based framework further demonstrates potential for broader applications, such as mental health monitoring, adaptive learning systems, and social media analytics.

However, this study has limitations, including a relatively small dataset with only three sentiment categories, which may reduce emotional granularity. Future work should address dataset expansion, diverse emotion labels, and improved generalization through advanced learning techniques[19], [20]. Enhancing the recommendation algorithm, increasing content variety, and adding features such as multimedia previews and notifications are also suggested to improve personalization and engagement. Continuous evaluation through analytics and user feedback is recommended to further optimize VibeScreen's performance and adaptability.

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