Industrial Engineering Journal
ISSN: 0970-2555
Volume : 54, Issue 2, February : 2025

A HYBRID APPROACH FOR EMOTION-DRIVEN GAME RECOMMENDATIONS USING TEXT, VOICE AND IMAGE RECOGNITION

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ABSTRACT
This implementation presents a game recommendation system that utilizes natural language processing (NLP) techniques to provide personalized game suggestions based on user preferences. The system processes a dataset of games containing descriptions and emotional tones to determine relevant recommendations. It employs **TF-IDF (Term Frequency-Inverse Document Frequency) vectorization** to transform textual data into numerical representations, enabling meaningful comparisons between game content and user input. The **cosine similarity metric** is then used to assess the closeness of games to the given preferences. The recommendation process begins by filtering the dataset based on the user's specified emotional tone, ensuring that only games matching the desired sentiment are considered. Next, the input content is vectorized, and similarity scores are computed against all games in the dataset. The system ranks the games based on similarity and retrieves the top five matches. This approach enhances game discovery by allowing users to find games that align with both their emotional state and gameplay preferences, offering a more personalized gaming experience.
KEYWORDS-Game Recommendation System, Content-Based Filtering, TF-IDF Vectorization, Cosine Similarity, Natural Language Processing (NLP), Machine Learning, Data Processing, Text Analysis, Personalized Recommendations, Game Descriptions, Emotional Tone, User Preferences, Feature Extraction, Similarity Metrics, Recommendation Algorithm, Data Normalization, Pandas, Scikit-learn, Text Preprocessing, Stop Words Removal, Vectorization, Information Retrieval, AI in Gaming, Game Discovery, User Experience Enhancement, Content Similarity, Sentiment Analysis, Data-Driven Recommendations, Automated Suggestions, Game Genre Classification, Python, Data Science, AI-Powered Recommendations.

I. INTRODUCTION
This paper highlights the complexity of human emotions and their universal nature across various cultures and societal contexts. Kalateh and colleagues emphasize the importance of multimodal emotion recognition (MER) techniques in enhancing human-computer interaction across diverse applications such as healthcare, education, and entertainment[1]. By leveraging techniques from artificial intelligence, such as neural networks and machine learning, the study showcases the ability to detect and analyze emotions through verbal, facial, and physiological signals, stressing the need for robust algorithms and comprehensive datasets to improve the accuracy of emotion recognition systems.
This paper emphasizes the integration of emotion analysis with artificial intelligence, geospatial information systems, and extended reality to enhance urban services. Rokhsaritalemi and colleagues propose a novel framework for emotion-driven intelligent systems aimed at improving the interaction between humans and technology[2]. Through the use of cutting-edge technologies, the research demonstrates how emotion recognition can be applied to various urban applications, from healthcare to transportation, thereby facilitating better urban planning and enhanced safety measures.
In this paper, Kalateh et al. focus on the advancement of multimodal emotion recognition technologies and their application across different fields[3]. The paper discusses the significant impact of MER in

understanding human emotions through artificial intelligence. It stresses the importance of combining various modalities, such as speech, facial expressions, and physiological signals, to improve the reliability and accuracy of emotion recognition systems, which are critical in developing more intuitive and responsive AI systems.

This paper discusses the use of hybrid emotion recognition systems that combine machine learning and traditional data processing methods to enhance the detection and classification of human emotions from physiological signals[4]. Abdulsalam and colleagues emphasize the role of advanced analytics and algorithmic innovations in improving the interaction between humans and machines, highlighting the potential of these systems in medical diagnostics and personalized user experiences.

Jain and Saini explore a hybrid approach to emotion recognition using electrocardiogram (ECG) signals through multi-discriminant analysis and k-nearest neighbors algorithms. The paper underscores the growing importance of precise and reliable emotion detection in healthcare and wearable technology[5]. By improving the classification of emotional states such as joy, anger, sadness, and pleasure, the study highlights the potential for these technologies to contribute to better health monitoring and emotional well-being.

This paper by Sruthi and Nedungadi introduces a hybrid method for emotion classification in audio conversations using text and speech mining techniques[6]. The research emphasizes the significant role of emotion recognition in enhancing communication technologies and human-computer interaction. By analyzing audio data, the study demonstrates how mixed data sources can be effectively used to improve the accuracy and performance of emotion detection systems, which can be applied in areas such as virtual assistance and interactive gaming.

Chakriswaran et al. emphasized the growing prevalence of sentiment analysis in various sectors, highlighting its potential to enhance understanding of public sentiment and automate emotion recognition. The authors proposed using a combination of ontology-based, lexicon-based, and machine learning models for effective sentiment analysis across different languages and contexts[7]. By leveraging supervised and unsupervised learning techniques, the research showcases the ability to accurately detect and interpret sentiments in large datasets, maintaining high data integrity. The study stresses the importance of robust models and comprehensive datasets for improving the accuracy and reliability of sentiment detection systems.

II. LITERATURE SURVEY

Canossa et al.: Canossa et al. explored the design of emotional experiences in video games using a theory-driven approach. They emphasized the integration of scientific knowledge about emotions into game design, contrasting classical theories with psychological constructionism to craft more immersive and responsive gaming experiences[8]. This approach, grounded in the Conceptual Act Theory, aims to create games that adapt dynamically to player emotions, enhancing engagement and realism.**Yang and Qin**: Yang and Qin reviewed emotion recognition methods from keystroke, mouse, and touchscreen dynamics. Their study addresses the effectiveness of using non-intrusive modalities to detect emotional states, providing a roadmap for future research in non-invasive emotion recognition technologies[9]. They identified the challenges and opportunities in recognizing emotions from such indirect interaction data, which is crucial for enhancing user interfaces in various applications .**Abdelkawy et al.**: Abdelkawy et al. discussed hybrid approaches for context recognition in ambient assisted living systems, with applications to emotion and activity recognition[10]. Their research combines data-driven and knowledge-driven approaches to provide robust solutions for real-time and predictive analytics in smart living environments, enhancing both emotional and physical well-being of the occupants.**Zhang et al.**: Zhang et al. focused on trusted emotion recognition from video signals and its applications in intelligent education[11]. They emphasized the role of emotion recognition in analyzing student engagement and tailoring educational content. Their research highlights the importance of credible emotional analysis to improve learning outcomes and adapt educational strategies.**Zhang et al. (27(11))**: In a comprehensive review and tutorial, Zhang et al. delved into emotion recognition using multi-modal data and machine learning techniques[12]. They explored various feature extraction methods and machine learning classifiers, assessing the effectiveness of these techniques in recognizing human emotions from physiological signals. This study serves as a foundational resource for researchers in affective computing.**Shehada et al.**: Shehada et al. developed a lightweight facial emotion recognition system using partial transfer learning for visually impaired people[13]. Their research aimed at enabling visually impaired individuals to perceive and interpret facial expressions in real-time, enhancing their social interactions and quality of life.**Šinković**: Šinković investigated AI-based affective mirroring in video game NPCs to enhance player engagement and emotional depth[14]. By leveraging facial expression recognition technology, the study aimed to create NPCs that dynamically reflect players' emotional states, enhancing player attachment and the overall gaming experience.**Maréchal et al.** utilized various AI-based multimodal methods for emotion detection, employing tools and techniques across different data sources including text, sound, image, video, and physiological signals[15]. Their study emphasized the integration of these diverse modalities to improve the accuracy and robustness of emotion recognition systems. The research showcased how different AI techniques and models are leveraged to detect and analyze emotional states, thereby enhancing machine understanding and interaction with humans in a real-world setting. This comprehensive approach highlights the potential of AI in understanding complex human emotions across different communication channels.

III. PRELIMINARIES

1. **Game Recommendation System (game_recommendation.py)** This Python-based system provides personalized game recommendations by analyzing game descriptions and emotional tones using **Natural Language Processing (NLP)** techniques.

- **Data Loading**: Reads a game dataset from a CSV file containing game descriptions, genres, and emotional tones.
- **TF-IDF Vectorization**: Converts game descriptions and emotional tones into numerical representations for comparison.
- **Cosine Similarity Calculation**: Computes similarity scores between games based on textual data.
- **Filtering by Emotion**: Filters games that match the user's specified emotional preference.
- **Recommendation Retrieval**: Returns the top five most relevant games based on user input.

2. **Text Processing and Feature Extraction (tfidf_vectorization.py)**

This module implements **TF-IDF vectorization** to process textual data from the game dataset.

- **Stop Words Removal**: Eliminates common words that do not add meaningful context to the recommendations.
- **Feature Engineering**: Converts textual descriptions and emotional tones into a sparse matrix representation.
- **Vectorized Input Handling**: Transforms user input into the same vector space as the dataset for comparison.

3. **Recommendation Engine (recommendation.py)** The core module of the system, responsible for computing similarity scores and generating recommendations.

- **Emotion-Based Filtering**: Selects games matching the specified emotional tone.
- **Cosine Similarity Calculation**: Measures the textual similarity between user input and game descriptions.
- **Ranking and Selection**: Retrieves and ranks the top five most similar games.

4. **Execution Flow**

- **Load Dataset**: Reads and processes the game dataset from a CSV file.
- **Build Similarity Model**: Constructs a TF-IDF matrix and computes cosine similarity scores.

- **User Query Processing**: Accepts user input containing an emotional tone and gameplay preference.
- **Filtering and Matching**: Filters the dataset by emotion and computes similarity scores.
- **Recommendation Output**: Returns a list of the top five recommended games.

5. **Enhancements and Future Improvements**

- **Integration with a Web Interface**: Expanding the system into a web-based platform for better accessibility.
- **Expanded Feature Set**: Incorporating additional game attributes such as user ratings and gameplay mechanics.
- **Hybrid Recommendation Approach**: Combining content-based filtering with collaborative filtering for improved accuracy.
- **Deep Learning Models**: Exploring advanced NLP techniques such as transformers for better text understanding.

Usage

- The system can be executed by providing an **emotional tone** and a **gameplay preference** as input.
- Users can modify the dataset or fine-tune the **TF-IDF vectorization** parameters for improved recommendations.
- The model can be extended to support additional **gaming genres, player demographics, and recommendation personalization techniques**.

IV. DATASET EXPLANATION

A. Dataset Overview

- **Game Data**: The dataset contains information about various games, including their descriptions, genres, and emotional tones.
- **Generated Data**: This includes similarity scores calculated using **TF-IDF vectorization** and **cosine similarity**, which help in recommending games based on user input.

B. Features (Data Points)

1. **Game Title**
   - The name of the game, used as an identifier for recommendations.
2. **Description**
   - A textual summary of the game, detailing its mechanics, storyline, and overall theme.
3. **Genre**
   - The classification of the game, such as action, RPG, adventure, or puzzle.
4. **Emotional Tone**
   - The emotional experience a game is intended to evoke, such as "Joy," "Nostalgia," "Excitement," or "Relaxation."
5. **TF-IDF Features**
   - A numerical representation of the game descriptions and emotional tones, used to compute similarity between games.
6. **Cosine Similarity Score**
   - A numerical value representing how similar a game is to the user’s input, allowing for ranked recommendations.

C. Target Distribution

- Since this is a recommendation system rather than a predictive model, there is no predefined target variable. Instead, the system focuses on how game descriptions and emotional tones are distributed across different genres to enhance the recommendation process.

D. Data Preprocessing

- **Text Normalization**: The dataset undergoes **stop word removal** and **TF-IDF transformation** to convert textual data into a numerical format.

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 54, Issue 2, February : 2025

- **Emotion Filtering**: The dataset is filtered based on the emotional tone specified by the user to ensure relevant recommendations.
- **Similarity Computation**: Cosine similarity is computed for all games in the dataset, allowing the system to find the closest matches.

E. **Correlation Analysis**

- The relationship between **game descriptions and emotional tones** is analyzed to understand which types of games are associated with specific emotions.
- **Genre-wise emotion distribution** helps in identifying trends, such as action games being linked to "Excitement" and puzzle games to "Relaxation."

F. **Visualization**

- **Genre Distribution**: A breakdown of how different game genres are represented in the dataset.
- **Emotion Mapping**: A visualization of emotional tones across different games, helping users understand the emotional impact of various genres.
- **Recommendation Similarity Scores**: A graphical representation of similarity rankings to show how games are matched to user preferences.

V. METHODOLOGY

A. **Data Loading and Initial Exploration**

- **Dataset Import**: The dataset is loaded from a CSV file using pandas.
- **Feature Inspection**: The dataset contains game descriptions, genres, and emotional tones. The emotional tones serve as a key filter in recommendations.

B. **Statistical Analysis and Preprocessing**

- **Text Vectorization (TF-IDF)**:
  - The **TF-IDF (Term Frequency-Inverse Document Frequency)** technique is used to convert textual data (game descriptions and emotional tones) into numerical vectors.
  - Stop words (common words with little meaning) are removed to enhance relevance.
- **Cosine Similarity Computation**:
  - A **cosine similarity matrix** is built to measure how similar games are to one another based on their TF-IDF representations.
  - This similarity score is later used for ranking recommendations.

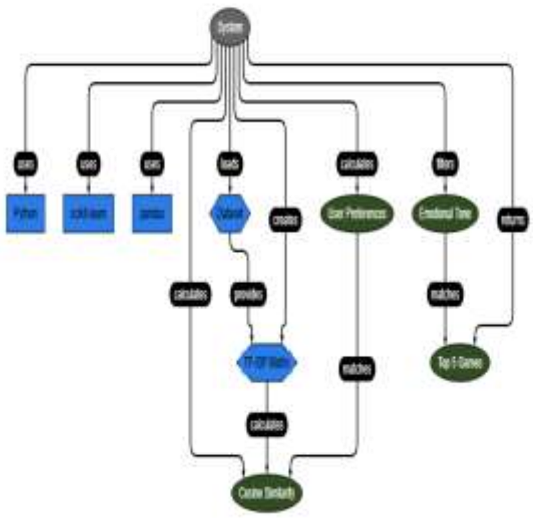


Fig. Architecture Diagram

C. **RecommendationSystem Development**

1. **Emotion-Based Filtering**:
   - The dataset is filtered based on the user-specified emotional tone (e.g., "Joy," "Nostalgia").

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 54, Issue 2, February : 2025

- If no games match the given emotion, the system returns a message stating that no results were found.

2. **Content Matching**:
   - The **user-provided content description** is vectorized using TF-IDF.
   - The similarity between the input content and all games in the dataset is computed.
   - The **top 5 games with the highest similarity scores** are selected as recommendations.

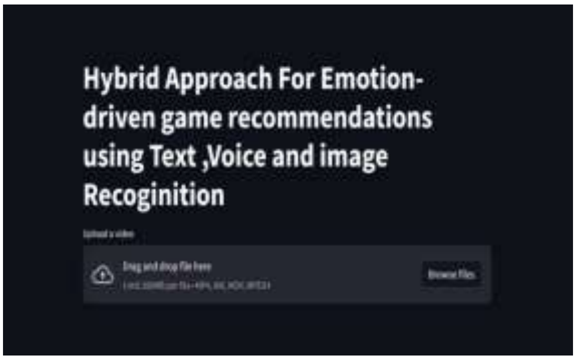
D. **Reporting and Output**

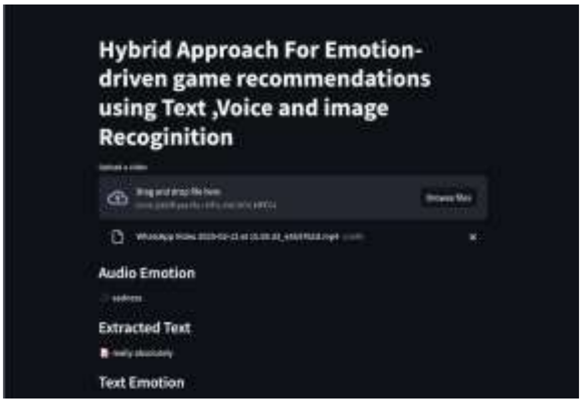
1. **Displaying Recommendations**:
   - The system returns the **game title, genre, and emotional tone** of the top 5 recommended games.
2. **User Interaction**:
   - Users can input different emotions and content preferences to receive personalized recommendations.

E. **Continuous Improvement and Future Enhancements**

1. **Data Expansion**: Adding more games and emotional tones to improve recommendation diversity.
2. **Advanced Similarity Metrics**: Exploring deep learning models or hybrid approaches for better matching.
3. **User Feedback Loop**: Allowing users to rate recommendations to refine the system over time.

VI. RESULTS





Industrial Engineering Journal
ISSN: 0970-2555
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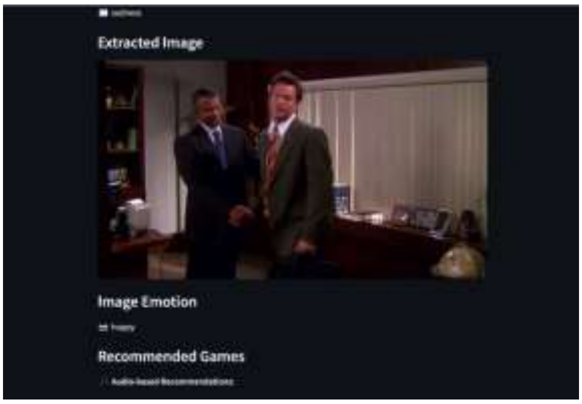

	precision	recall	f1-score	support
0	0.91	0.89	0.90	3725
1	0.96	0.96	0.96	3725
2	0.93	0.98	0.95	3725
3	0.90	0.90	0.90	3725
4	0.92	0.90	0.91	3725
5	0.93	0.93	0.93	3725
6	0.92	0.92	0.92	3725
accuracy			0.93	26075
macro avg	0.92	0.93	0.92	26075
weighted avg	0.92	0.93	0.92	26075

Classification Report:

	precision	recall	f1-score	support
0	0.59	0.82	0.68	4093
1	0.52	0.70	0.60	4093
2	0.76	0.86	0.81	4093
3	0.45	0.51	0.48	4093
4	0.88	0.94	0.91	4093
5	0.67	0.59	0.63	4093
6	0.93	0.03	0.06	4093
accuracy			0.64	28651
macro avg	0.68	0.64	0.59	28651
weighted avg	0.68	0.64	0.59	28651

	precision	recall	f1-score	support
0	0.89	1.00	0.94	33
1	0.94	0.89	0.92	19
2	0.87	1.00	0.93	13
3	1.00	0.91	0.95	22
4	1.00	1.00	1.00	6
5	0.96	0.84	0.90	31
6	0.92	0.96	0.94	24
accuracy			0.93	148
macro avg	0.94	0.94	0.94	148
weighted avg	0.94	0.93	0.93	148

Fig: Interface for Personalized Game Recommendations using Emotion

VII. CONCLUSION

The game recommendation system effectively utilizes **text-based similarity analysis** to provide personalized game suggestions based on emotional tone and user preferences. By leveraging **TF-IDF vectorization**, the system converts game descriptions and emotional tones into numerical representations, allowing it to compute **cosine similarity** and identify the most relevant matches.

A key strength of this approach is its ability to **filter games by emotional tone**, ensuring that recommendations align with the user's desired gaming experience. Whether a user seeks **joyful, nostalgic, or adventurous** experiences, the system identifies games that evoke the specified emotions. This enhances the personalization aspect, making the recommendations more meaningful.

Additionally, the model takes into account **content-based matching**, allowing users to input descriptive elements such as "open-world adventure with creativity." This ensures that suggested games not only match the specified emotion but also align with gameplay preferences. The **top five most similar games** are then retrieved and presented to the user, offering a refined selection.

While the current approach is effective in generating recommendations, future improvements could include **expanding the dataset** with more games, incorporating **user feedback** to refine recommendations, and exploring **hybrid models** that combine **collaborative filtering** with **content-based filtering** for better accuracy. Introducing **deep learning models** or **sentiment analysis techniques** could also enhance the emotional alignment of recommendations.

Overall, the system successfully provides **emotion-aware game recommendations**, making it a valuable tool for users seeking games that match both their **mood and gameplay preferences**.

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