MoodShelf: An Emotion-Based Book Recommender System

Yuri Anton S. Cariscal
College of Information and Computer Studies
De La Salle University - Dasmarinas
CYS0775@dlsud.edu.ph

Christian Elijah DC. Darvin
College of Information and Computer Studies
De La Salle University - Dasmarinas
dcd0655@dlsud.edu.ph

Xian Angel B. Palomares
College of Information and Computer Studies
De La Salle University - Dasmarinas
PXB0696@dlsud.edu.ph

ABSTRACT

This study presents MoodShelf, a novel emotion-based book recommender system designed to enhance readers' engagement by aligning book recommendations with their emotional preferences. Utilizing the DistilRoBERTa model from Hugging Face, the system analyzes book descriptions to classify emotional content into seven categories: anger, disgust, fear, joy, neutral, sadness, and surprise. If users have prior reading experience, the system identifies emotional patterns in their reviewed books; otherwise, users can input desired emotional states to receive personalized recommendations. The evaluation of the model's emotion classification showed an overall accuracy of 43%, with stronger performance in more frequent categories such as fear (F1-score: 0.59), neutral (0.52), and joy (0.45). However, the system encountered difficulty in recognizing less distinct emotions like disgust (0.11) and surprise (0.22), suggesting further refinements are needed to handle nuanced emotional cues more effectively.

KEYWORDS

emotion-based recommendation, book recommender system, DistilRoBERTa, affective computing, content-based filtering, emotional intelligence, personalized reading, Hugging Face, natural language processing

1. INTRODUCTION

As more people become interested in reading books, the global book market has seen steady growth, driven by rising demand for personalized and emotionally engaging reading experiences. This expansion is especially notable in digital and audio formats, reflecting a shift toward convenience and accessibility. However, some European countries faced a declining bookstores sale due to inflation. In the Philippines, there is a steady decline of readership among Filipinos. According to the 2023 National Readership Survey (NRS) commissioned by the National Book Development Board (NBDB) and conducted by the Social Weather Stations (SWS), the percentage of Filipinos who read books and other materials not required for school has declined. The 2023 National Readership Survey, which included 4,800 respondents consisting of 2,400 adults (aged 18 and over) and 2,400 children (aged 8 to 17), revealed that only 42% engaged in non-school book reading in the past year. This marks a notable 12-point decline from the 54% reported in a similar survey conducted in 2012. The scarcity of libraries, difficulty of finding time to read, expensive cost of books, and distractions were the main causes of this decline.

Usluoğlu (2024) highlighted that recent research underscores a significant link between reading fiction, especially literary fiction, and an enhanced ability to understand the mental states of others. This connection is supported by diverse psychological studies including relational, neuroimaging evidence and carries implications for supporting healthy individuals' social cognition as well as for potential clinical assessment and intervention. Liu et al., (2023) found that reading significantly reduces work stress and enhances job satisfaction. The study utilized a psychological effect regression model and multivariate linear regression to analyze the relationship, addressing endogeneity issues. This research offers strategic recommendations for individuals and organizations and contributes to theoretical understanding in stress management and career development.

The objective of this study is to develop a recommendation system that analyzes user book reviews to identify prominent emotions and recommend books that evoke similar emotional responses. Alternatively, if the user hasn't read a book, they can specify the desired proportions of emotions they wish to experience, and the system will recommend books accordingly. This study utilizes the Hugging Face model Emotion English DistilRoBERTa-base, which analyzes and categorizes the emotional content of user book reviews. It is based on Paul Ekman's six basic emotions along with one additional class: anger, disgust, fear, joy, neutral, sadness, and surprise.

While readers can find recommended books through social media and book clubs, the researchers believe that adding an emotional criterion based on what readers want to feel while reading makes the experience more engaging beyond just the book’s popularity. Readers might struggle to find books that match what they want to read, which is why the researchers aim to develop MoodShelf, a web application that provides users with popular books based on the emotions they wish to experience.

2. RELATED WORKS

An extensive review of relevant literature is presented in this chapter with a view to building a strong theoretical and empirical basis for the emotion-based book recommender system using

DistilRoBERTa. The fundamentals of sentiment analysis, recommendation algorithms, and natural language processing are discussed, along with prior work and several key theoretical frameworks. This review looks at different academic views and examines the gaps in the research, which stresses the need for emotion-aware recommendation systems. This chapter places the current studies in the current broader academic conversation regarding personalized and AI-driven book recommendations through a critical analysis of related studies and how the current studies contribute to this evolving discourse.

In recent years, book recommendation systems have improved greatly in both areas of personalization and accuracy of recommendations, using a combination of data mining, artificial intelligence and user modelling techniques. These systems are further categorized as six distinct classes and mapped into the current trends, challenges, and evaluation methodologies as outlined in Alharthi, Inkpen, and Szpakowicz (2018) in their comprehensive survey. The importance of enriching recommendation effectiveness by including psychological insights on how to read readers' preferences and behavior is highlighted. Likewise, Anwar, Siddiqui, and Sohail (2020) investigate the increasing application of machine learning techniques to book recommender systems. They cover collaborative filtering, content-based filtering, and hybrids, covering common evaluation criteria like precision, recall, and RMSE. Taken together, these surveys present an overview of the evolution as well as the current landscape of book recommendation technologies from an interdisciplinary and computational innovation perspective.

In several studies, hybrid models that combine different recommendation approaches are proposed to work around typical issues such as cold start problems and data sparsity and to scale to large datasets. Fatarphekar et al. (2015) developed a hybrid book recommendation system that mixes content-based filtering, collaborative filtering, and association rule mining in order to boost the relevance of recommendations in online book-selling platforms. The study A Novel Approach for Book Recommendation Systems does exactly this, taking a similar direction and integrating all three techniques to enhance personalization. These systems combine the pattern discovery of association rule mining with the analytical power of content- and collaborative-based recommendation methods and produce more accurate and context-aware recommendations.

An Improved Online Book Recommender System using Improved Collaborative Filtering Algorithm: 2018 focused on algorithmic improvements on an enhanced system using an enhanced collaborative filtering method, but with object-oriented analysis & design methodology (OOADM). The system has been implemented using Django and Firebase with scaling in mind as well as real-time data handling. With an efficient quick sort algorithm and a judicious way to filter the students' information, the system was able to achieve an RMSE-based recommendation accuracy of 90% to 95%. The results highlight that it is possible to build robust, high-performance, and scalable recommendation systems by jointly supporting backend robust design and advanced algorithms.

Novel approaches are being explored beyond traditional hybrid techniques, which include user psychology and personal attributes. Hariadi and Nurjanah (2017) then introduce a unique hybrid recommendation system that combines content-based filtering with a personality-aware collaborative filtering technique, MSV-MSL (Most Similar Visited Material to the Most Similar Learner). They make use of both book attributes and user personality characteristics to create more subtle recommendations, specifically in situations when user item interaction data is limited. The system is able to achieve increased personalization by integrating user psychology into the recommendation process that results in higher user satisfaction and engagement.

In 2013, a study about 'Book Recommendation System Using Opinion Mining Technique,' states that people are increasingly using Internet applications in their daily lives, and they prefer online shopping for their needs, but for academicians, researchers, and students, purchasing the desired book from vast collections of books on the Internet is a time-consuming process. The study offered a recommendation technique based on opinion mining to propose top-ranked books in several computer science disciplines, which the researchers selected based on consumer needs and reviews. Because the researchers are recommending books, they did not obtain the names of the books from any bookstall. Instead, they searched for books in various disciplines of computer science in search engines such as Google, where these books were then searched again with a modified query to obtain book reviews and customer opinions on these books. The results demonstrate that, due to page constraints, just one topic, "cloud computing," is illustrated with results. These suggested ranked books are intended to be among the top books on the subject, and this work may be useful to millions of buyers looking for the greatest books on the market.

Another study, Introducing Hybrid Techniques for Optimization of Book Recommender System, was conducted in 2015, and it states that there are several online shopping portals offered by organizations such as Amazon, Flipkart, Snapdeal, Junglee, Jabong, and others, all of which are gaining online market share. As a result, effective business approaches must be implemented to handle the massive amount of data generated every day, and recommendation systems such as collaborative filtering, content-based, and demographic play a significant part in filtering this data and presenting appropriate information to users. In the findings of the investigations, it has been found that filtering suggestions in the hybrid approach has collaborative filtering, content-based, and demographic, and that users with unusual taste or preference affect the recommender system, noting that the number of ratings obtained is typically quite small in comparison to the number of ratings that must be projected, so recall diminishes as the number of users increases.

Another study from 2018 on 'Book Recommendation System through Content-Based and Collaborative Filtering Method' stated that rather than going out and buying items for themselves, online recommendations provide an easier and faster way to buy items, and transactions are also faster when done online. Proving that suggested systems are powerful new technologies that assist consumers in finding items they want to buy and that they are widely utilized to recommend the most relevant products to end users. The article proposes a Book Recommendation System (BRS) that uses a combination of content-based filtering (CBF), collaborative filtering (CF), and association rule mining to generate efficient and effective recommendations. As the researchers build their study, the main challenge is creating a new website application for book sales and implementing the appropriate recommendation module based on the user's interests, as well as coordinating and implementing both content-based filtering and collaborative filtering.

According to a 2012 study titled "Building a Book Recommender System Using Time-Based Content Filtering," while most time recommender systems are used in the online shopping and entertainment domains, such as movies and music, their applicability is also being researched in other areas. The paper also suggests a recommender system that integrates user decisions with not only similar users but also other users in order to provide various recommendations that evolve over time. After a certain length of time, the recommendation mechanism loses accuracy, and users continue to receive similar products. The results reveal that the proposed design for the book recommendation engine provides consumers with diversified and often updated recommendations that are more useful and relevant.

During the pandemic, in the year 2020, a study on 'Machine learning-based book recommender system' conducted surveys and new perspectives, in which the study stated that recommender systems are very useful in reducing information overload and providing users with the items of their need, specifically e-commerce, online auction, and book and conference recommendation for academia and industrialists. The results divide Machine Learning techniques into six categories: classification-based, k-nearest neighbor, support vector machine, neural network, association rule mining, and clustering-based.

Table 1. Synthesis Table

Authors	Application	Algorithms	Key Features	Results
Alharthi et al. (2018)	Survey of book recommender systems	CF, CBF, Hybrid	Categorizes six system types; explores challenges, datasets, and evaluation methods	Provides a broad framework; emphasizes psychological insight for personalization
Anwar et al. (2020)	Survey on ML techniques in recommender systems	ML-based CF, CBF, Hybrid	Reviews machine learning applications and metrics in recommendation systems	Highlights the effectiveness of ML for enhancing recommendation accuracy
Farkhod et al. (2022)	Personalized book suggestions	Content-Based Filtering, Collaborative Filtering	Uses user/book features and interaction history	Demonstrates improved relevance vs. standalone approaches
Roy & Singh (2018)	Time-sensitive book recommendation	Time-aware Content Filtering	Integrates timestamp data into filtering	Improves accuracy for temporally relevant recommendations
Singh et al. (2018)	Sentiment-driven recommendations	Opinion Mining, Hybrid Filtering	Applies NLP to user reviews to extract sentiment	Enhances relevance and user satisfaction
Sachdeva et al. (2019)	Optimized hybrid system	Hybrid (CF, CBF, Demographic Filtering)	Integrates demographic information into hybrid models	Offers better personalization; reduces cold-start issues
Chandaket al. (2018)	Scalable online book recommender system	Improved Collaborative Filtering, Quick Sort	Implements OOADM, Django, and Firebase for scalable, real-time performance	Achieves 90–95% accuracy using RMSE

Authors	Application	Algorithms	Key Features	Results
		Algorithm		
Fatarphekar et al. (2015)	Book recommendations for e-commerce	CBF, CF, Association Rule Mining	Combines three techniques to improve accuracy and efficiency	Overcomes sparsity; enhances recommendation relevance
Hariadi & Nurjanah (2017)	Personalized book recommendation using personality	Personality-aware CF, CBF (MSV-MSL)	Uses learner traits and content similarity to suggest books	Solves cold-start issue; aligns suggestions with personality
Devika et al. (2016)	Enhanced hybrid recommendation system	CBF, CF, Association Rule Mining	Integrates multiple methods to tackle common system challenges	Boosts user engagement and recommendation effectiveness

3. METHODOLOGIES

3.1 Equipment

This study utilized the following equipment: (1) personal computers and (2) internet. The model was trained using the Python programming language within a Jupyter Notebook environment. The web application was built with Streamlit. In order to track changes in the model or web application, Git was used as the version control system to track changes in both the model and the web application.

3.2 Data Collection

The datasets used in this research were obtained from Hugging Face, an AI community and platform that also serves as a social network for developers, academics, and enthusiasts. The Goodreads reviews dataset contains 53,994 entries, including book titles, authors, ratings, descriptions, genres, pages, number of ratings, and the percentage of users who liked each book. The emotion classification model was also sourced from Hugging Face, specifically the Emotion English DistilRoBERTa base model, which was trained to recognize emotions such as anger, disgust, fear, joy, neutral, sadness, and surprise.

3.3 Data Processing

The Goodreads reviews dataset contains 53,994 book entries; however, upon inspection, 11,821 duplicate entries were found and removed, resulting in a total of 42,123 unique book entries. The book descriptions were preprocessed using the NLTK library by tokenizing the text, removing stop words, and filtering out irrelevant information. Since the dataset does not include user reviews, a Python function was implemented to classify the emotions evoked by each book description. This was achieved using the pre-trained Hugging Face model, which assigns one of seven emotion labels: anger, disgust, fear, joy, neutral, sadness, and surprise based on textual input. The function processes the descriptions in batches, tokenizes the text using the appropriate RoBERTa tokenizer, and performs inference with the emotion classification model. The output probabilities are passed through a softmax layer, and the emotion with the highest probability is selected as the predicted label for each description.

3.4 Model Architecture

The model used in this study is DistilRoBERTa, a distilled version of the RoBERTa transformer-based language model. DistilRoBERTa retains the core architecture of RoBERTa but reduces its size and complexity to achieve faster and more efficient inference. The model has 6 layers, 768 dimension and 12 heads, totalizing 82M parameters (compared to 125M parameters for RoBERTa-base). On average DistilRoBERTa is twice as fast as Roberta-base.

Knowledge distillation is a compression technique where a compact model, such as a student, is trained to replicate the behavior of a larger model, such as a teacher or ensemble of models. In supervised learning, a classification model is trained to predict instances by maximizing the probability of labels. The standard training objective is to minimize cross-entropy between the model's predicted distribution and the one-hot empirical distribution of training labels.

Masked Language Model (MLM) uses a random sample of tokens in an input sequence to predict masked tokens. BERT randomly selects 15% of these tokens for replacement, with 80% being masked, 10% unchanged, and 10% a vocabulary token. The original implementation performed random masking and replacement once, but data is duplicated, causing the mask to change for each training sentence.

Next Sentence Prediction (NSP) is a binary classification loss that predicts if two segments follow each other in the original text. It creates positive examples by taking consecutive sentences from the text corpus and negative examples by pairing segments from different documents.

3.5 Algorithm

3.5.1 DistilRoBERTa

DistilRoBERTa is a smaller and faster version of the RoBERTa model. RoBERTa, developed by Facebook AI, is an improved version of Google's 2018 BERT model, sharing the same architecture. DistilRoBERTa applies knowledge distillation to RoBERTa, creating a more efficient model with fewer parameters (6 transformer layers instead of 12), faster inference speed, and reduced computational resources while retaining approximately 97% of RoBERTa's accuracy.

Distillation Loss measures the difference between the probability distribution predicted by the student model (DistilRoBERTa) and the "soft targets" (softmax output probabilities) generated by the teacher model (RoBERTa). It typically uses a Kullback-Leibler (KL) divergence between the student's and teacher's softmax outputs, often applied with a temperature scaling parameter (T) to soften the probability distributions.

$$L_{distil} = \sum_{i} KL(P_T(i,T) \,||\, P_S(i,T))$$

where:

$P_T(i,T)$ is the probability distribution over classes for input i predicted by the Teacher model, with temperature T

$P_S(i,T)$ is the probability distribution over classes for input i predicted by the Student model (DistilRoBERTa), with temperature T

T is the temperature parameter that smooths the probability distribution

KL is the Kullback-Leibler divergence

Masked Language Modeling Loss is where the student model is concurrently trained which forces it to learn robust language representations independently.

$$L_{MLM} = -\sum_{j \in masked} \log\left(P\left(x_j | context\right)\right)$$

where:

x_j is the true token for the jth masked position

$P\left(x_j | context\right)$ is the probability predicted by the student model for x_j given the surrounding context

Total training loss for DistilRoBERTa is a weighted sum of the Distillation Loss and Masked Language Modeling Loss

$$L_{total} = \alpha * L_{distil} + \beta * L_{MLM}$$

where:

α and β are hyperparameters that balance the contribution of each loss term

3.5.2 Content-Based Filtering

Content-based filtering is an approach that recommends items to the user by comparing the attributes and features of the items the user has interacted with or shown interest in. With an examination of attributes such as genre, author, keywords, or other metadata, this method identifies relationships between items to suggest new content that closely resembles a user's previous interests. It runs independently of the data of other users, lending it to settings where personalized recommendations are desired but where the collaborative data is scarce or nonexistent. Content-based filtering is one of the most common techniques employed in book recommender systems to personalize recommendations based on a user's interests, which will increase the relevance and satisfaction of recommendations.

For two vectors, A and B, the cosine similarity is calculated as:

$$Cosine\ Similarity(A,B) = \frac{A * B}{|A||B|}$$

where:

$A * B$ is the dot product of vectors A and B.

$|A|$ and $|B|$ are the Euclidean magnitudes (L2 norms) of vectors A and B

3.6 Evaluation and Comparison

The evaluation of the developed emotion classification model was conducted using both quantitative metrics and visual analysis techniques to assess its learning behavior and predictive performance. Quantitative evaluation involved tracking precision, recall, and F1 score across each emotional category, alongside overall accuracy. These metrics provided insight into how well the model differentiated between various emotional expressions, particularly in the presence of class imbalance and overlapping features.

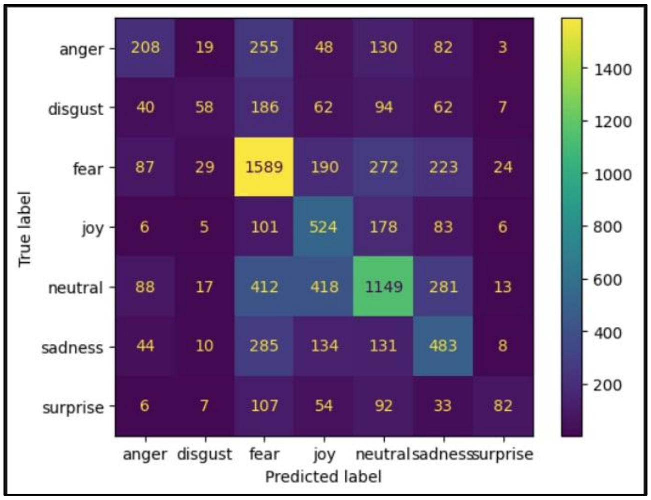
4. RESULTS AND DISCUSSION

4.1 Model Performance

The evaluation of the model's ability to classify emotional categories was carried out using a standard set of classification metrics, including precision, recall, and F1-score. The model achieved an overall accuracy of 43%, with a macro-average precision, recall, and F1-score of 39%, 40%, and 40%, respectively. The weighted average scores were higher, at 48% for precision, 49% for recall, and 49% for F1-score, reflecting the model's stronger performance on more frequently occurring classes.

The classification report indicates that the model performed best in identifying fear, achieving the highest F1-score of 0.59 across 2,414 instances. This suggests that the model has learned more robust representations for this class. This is followed by neutral and joy, which yielded F1-scores of 0.52 and 0.45, respectively.

Figure 1: Confusion Matrix – Random Forest Classifier



The confusion matrix further illustrates the model's performance. Notably, a large number of neutral instances were misclassified as joy (418), and many fear instances were confused with neutral (272) and sadness (223). Similarly, anger was frequently mistaken for fear (255 times) and neutral (130 times), showing a trend of confusion among adjacent or overlapping emotional states. This overlap may be attributed to the inherently subjective and context-dependent nature of emotional expression in the data, where lexical cues may ambiguously signal multiple emotions.

5 CONCLUSION AND FUTURE WORKS

5.1 Conclusion

In summary, the emotion classification model evaluated in this study demonstrates a foundational capability in recognizing emotional patterns from text, particularly in more frequently occurring categories such as fear, neutral, and joy. With an overall accuracy of 43% and relatively balanced weighted performance metrics (precision, recall, and F1 score at approximately 49%), the model reflects moderate effectiveness in handling the complexities of emotion detection. However, the notable drop in performance for categories like disgust and surprise, both achieving F1 scores below 0.25, underscores the difficulty in distinguishing between more nuanced or underrepresented emotions. Moreover, the evaluation process highlighted valuable user feedback centered on enhancing the model's accuracy, expanding the range of detectable emotions, and improving the user experience. Users also expressed the need for clearer emotion differentiation and more visually

Emotions such as sadness and anger performed moderately with F1-scores of 0.44 and 0.31. However, the model struggled significantly in identifying disgust and surprise, with F1-scores of 0.11 and 0.22, respectively highlighting challenges in differentiating less distinct or more nuanced emotional cues.

engaging outputs, suggesting a preference for improvements in analytics representation and interface interaction.

5.2 Future Works

Aside from offering book recommendations, numerous significant obstacles exist in the field of book recommender systems which can include facilitating online book in store, integrating elements like this may improve the overall recommendation experience and contribute to future system advancements.

In the near future, the researchers plan to expand our research to include a wider range of datasets such as movies, fashion, literature, humor, and others in order to identify the best data sources for our suggested methodology. Another intriguing avenue for investigation is the incorporation of user personality factors into recommendation systems. Moving forward, we intend to completely integrate personality-based modeling, including a thorough training process, to examine its potential to improve suggestion accuracy and user happiness.

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