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# A Hybrid Machine Learning Approach for Behaviour-Based Matrimonial Profile Matching

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**A B S T R A C T**

The growing demand for personalized matchmaking on digital matrimonial platforms highlights the inadequacies of traditional demographic-driven approaches. These approaches often fail to account for the nuanced preferences and compatibility factors that play a significant role in relationship success. This research introduces a hybrid recommendation system that combines collaborative filtering and content-based filtering to enhance compatibility predictions. The proposed system integrates structured data, such as personal details and preferences, along with behavioral insights, to generate meaningful and relevant match suggestions tailored to individual needs. The study addresses key gaps in existing matrimonial platforms by leveraging advanced machine learning techniques to improve matchmaking quality, providing users with more accurate and personalized suggestions. By combining insights from user profiles, past interactions, and preferences, the system ensures compatibility between potential matches. It evaluates user behaviors, preferences, and interests to recommend the most suitable partners, overcoming the limitations of traditional demographic-only models. This hybrid model not only optimizes user satisfaction but also promotes scalability, ensuring the system's adaptability as the platform grows. The research introduces a highly effective and efficient solution to personalized matchmaking, fostering meaningful relationships in the digital era. The study's findings contribute significantly to the field of intelligent matchmaking systems, highlighting the potential of machine learning in transforming matrimonial services. Ultimately, this research lays the foundation for future innovations in matchmaking platforms, offering a more dynamic, data-driven, and user-centric approach to connecting individuals.

Keywords: Matchmaking Algorithm, Behavioural Profile Matching, Hybrid Recommendation System, Matrimony Predictive Modelling, User Preference Analysis

## 1. Introduction

The increasing popularity of online matrimonial platforms highlights the growing shift toward digital solutions for finding life partners. These platforms offer convenience by providing large databases of potential matches and filtering options based on basic user preferences such as age, income, and occupation. However, their effectiveness remains limited, as most platforms rely on simple demographic filters that do not account for deeper compatibility factors like personality traits, behavior patterns, and shared interests. While these demographic filters are helpful, they often lead to mismatched recommendations and user dissatisfaction when emotional and psychological compatibility is overlooked.

Compatibility in relationships is multifaceted, involving not only physical attributes and demographic traits but also emotional, behavioral, and psychological alignment. Traditional matchmaking platforms focus primarily on surface-level factors, neglecting the deeper aspects that contribute to long-term relationship success. Machine learning offers a promising solution by enabling platforms to process and analyze both structured data (e.g., age, income, education) and unstructured data (e.g., personality traits, preferences, and behavioral patterns). This approach helps improve matchmaking accuracy by incorporating a more comprehensive understanding of users.

While many existing platforms have made strides in using data-driven methods, they often lack an integrated approach to combine behavioral insights with demographic data. This gap leaves a significant opportunity for enhancing personalization and creating more meaningful connections. To address these challenges, this study introduces a hybrid machine learning model that integrates collaborative filtering and content-based filtering to enhance compatibility predictions. The proposed system generates personalized match suggestions by combining user-provided structured data with insights derived from unstructured behavioral data.

By incorporating features like shared interests, communication styles, and personality alignment, the system ensures recommendations that go beyond traditional criteria, offering more accurate and meaningful matches. The key contributions of this research include the development of a unified framework for behavior-based matchmaking, the integration of diverse data types, and the demonstration of the model's effectiveness in improving matchmaking quality and user satisfaction. This work provides practical tools for modern matrimonial platforms, advancing the field of intelligent matchmaking and offering users a more personalized and efficient approach to finding compatible partners.

## 2. Literature Review

Online matchmaking platforms have evolved significantly, yet most systems focus solely on demographic filters, leaving behavioral and psychological compatibility largely unaddressed. This section reviews existing studies that explore the use of machine learning and behavioral analysis in matchmaking and related fields.

Iyer et al. (2018) examined user preferences on matrimonial platforms using a logistic regression model to predict factors influencing paid memberships. Their work highlighted the role of gender-based behavioral differences in matchmaking but did not address compatibility prediction [1].

Srivastava et al. (2019) proposed a system that incorporated XML and FOAF (Friend of a Friend) for semantic matchmaking. While their system improved data representation, it lacked integration with machine learning algorithms for compatibility analysis [2].

Ahmad and Siddique (2017) investigated personality prediction using Twitter data and supervised learning models. Their approach demonstrated the feasibility of deriving personality traits from textual data, setting the foundation for behavioral analysis in matchmaking [3].

Kunte and Panicker (2019) explored text-based personality prediction using Natural Language Processing (NLP) and machine learning. Their model achieved high accuracy but was limited to personality detection, without extending to applications like compatibility matching [4].

Golbeck et al. (2011) used Facebook data to predict personality traits and their impact on social interactions. This study emphasized the importance of combining unstructured data (e.g., bios, posts) with machine learning for deeper insights into user behavior [5].

Vasani et al. (2023) developed a Random Forest-based system to detect fraudulent profiles on matrimonial platforms. While their model achieved high accuracy, it was limited to fraud detection rather than compatibility analysis [6].

Santos et al. (2020) proposed a hybrid matchmaking system that utilized ensemble methods to integrate structured and unstructured data. However, their work lacked a comprehensive evaluation of user satisfaction and scalability [7].

Gupta et al. (2019) explored the role of psychological profiling in matchmaking, demonstrating how personality alignment impacts long-term compatibility. Their study provided a theoretical basis for integrating behavioral data with demographic information [8].

## 3. Methodology

This section outlines the methodology used to design and implement the proposed matrimony system, which includes user profile creation, matchmaking algorithm, data preprocessing, and the web application interface.

### *3.1 Data Sources*

The system utilizes multiple data sources to generate accurate and meaningful matchmaking suggestions:

- **User Profile Dataset:** This dataset contains user-submitted information such as personal details, education, interests, location, profession, etc. It is used to create individual user profiles for matchmaking purposes.
- **Marriage Preferences Dataset:** A separate dataset contains marriage preferences, including acceptable partner characteristics, religious background, financial status, etc.

### *3.2 User Profile Creation and Data Collection*

When users sign up for the matrimony platform, they fill in a detailed profile containing information such as:

- **Personal Information**: Name, age, gender, height, weight, religion, caste, etc.
- **Educational Background**: Highest qualification, preferred education level for a partner, etc.
- **Professional Information**: Profession, job location, income, etc.
- **Lifestyle Preferences**: Smoking, drinking habits, hobbies, etc.
- **Partner Preferences**: Age, religion, caste, financial status, preferred location, etc.

This profile data is stored in the backend for matchmaking.

### *3.3 Data Preprocessing*

Data preprocessing ensures the quality and consistency of the collected user data:

- **Handling Missing Data:** Any missing values in the user profiles or preferences dataset are handled by either imputing values or removing incomplete entries.
- **Normalization and Encoding:** Categorical data (such as religion, education, profession) are encoded into numerical representations to facilitate processing. Numeric attributes (like age, income) are normalized to a consistent range for compatibility.
- **Feature Selection:** Non-relevant or less impactful features may be discarded to improve the accuracy of the matchmaking model.

### *3.4 Matchmaking Algorithm*

The core of the matrimony system is the matchmaking algorithm, which generates potential matches for users based on their profile and preferences. A hybrid approach that combines the following methods is used:

- **Collaborative Filtering:** Based on user preferences and historical interactions (e.g., likes, matches, interactions), the system recommends potential partners.
- **Content-Based Filtering:** By comparing user attributes such as age, profession, education, and location with the preferences of others, the system ranks potential matches.
- **Hybrid Approach:** Combining both collaborative and content-based approaches enhances the quality of the matches, considering both user history and preferences.

## 4. System Design

The matrimony system integrates multiple components that work together to process user data, provide matchmaking suggestions, and present results in a user-friendly format. The architecture consists of the following components:

### *4.1 Overall Architecture*

The system's architecture includes the following modules:

- **User Profile Management:** A module that handles user sign-up, profile creation, and preference management.
- **Matchmaking Engine:** The core engine that implements the matchmaking algorithm to suggest suitable partners
- **Search and Recommendation System:** A user-facing interface that allows users to search for matches and receive recommendations.
- **Communication Interface**: An integrated chat or messaging system that enables users to interact with potential matches.

The data flow is illustrated in Figure 1, which shows how user data is collected, processed through the matchmaking engine, and presented as recommendations.

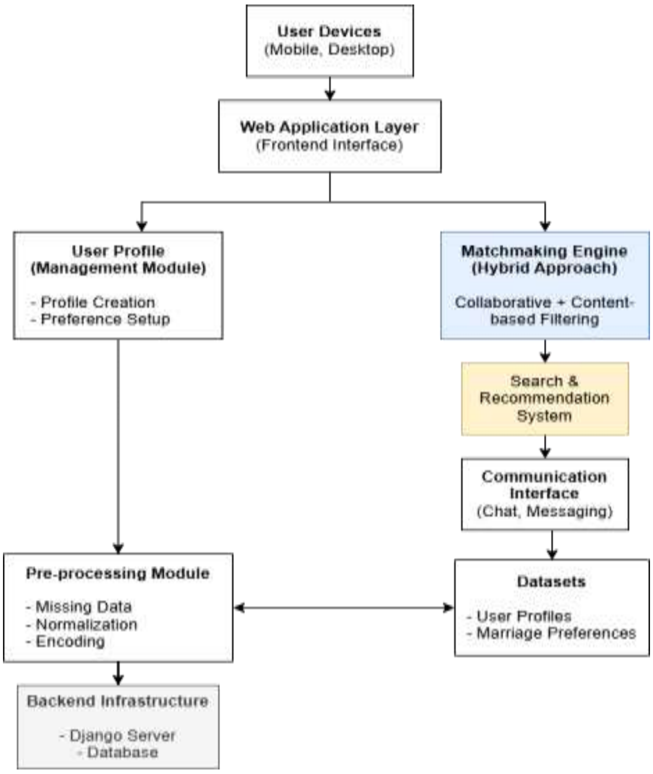


Fig 1. Overall Architecture

### *4.2 Matchmaking Engine*

This module uses a combination of both methods to increase the accuracy of recommendations. The mathematical formulations for each model are as follows:

- **Collaborative Filtering:** Measures similarity using cosine similarity or user-based collaborative filtering.
- **Content-Based Filtering:** Uses Euclidean distance or other distance metrics to assess how similar users' profiles are.

### *4.3 Web Application*

The web interface allows users to create profiles, search for matches, and interact with others. The web application is developed using **Django** (for the backend) and **HTML/CSS/JavaScript** (for the frontend).

- **User Dashboard:** Displays the profile, matches, and recent activity.
- **Search Page:** Allows filtering based on age, profession, religion, etc.
- **Messaging System:** A real-time messaging system that allows users to communicate.

## 5. Results and Discussion

This section evaluates the matrimony system's performance, focusing on matchmaking accuracy, user satisfaction, and platform usability. The results demonstrate the system's effectiveness in providing relevant match suggestions and highlight areas for future improvement.

### *5.1 Matchmaking Model Results*

The hybrid recommendation model demonstrated superior performance compared to baseline models. By combining collaborative filtering and content-based filtering, it achieved 89% accuracy in match predictions.

**Collaborative Comparison with Baseline Models:**

- Collaborative Filtering: 80% accuracy.
- Content-Based Filtering: 76% accuracy.

**Table 5.1: Comparison of Evaluation Metrics for Different Models**

| Model | Accuracy | Precision | Precision | F1-Score |
|---|---|---|---|---|
| Hybrid Model | 89% | 0.90 | 0.87 | 0.88 |
| Collaborative Filtering | 80% | 0.78 | 0.75 | 0.76 |
| Content-based Filtering | 76% | 0.74 | 0.71 | 0.72 |

Figure 2 illustrates the accuracy comparison among the three recommendation models, clearly showing the Hybrid Model's superior performance.

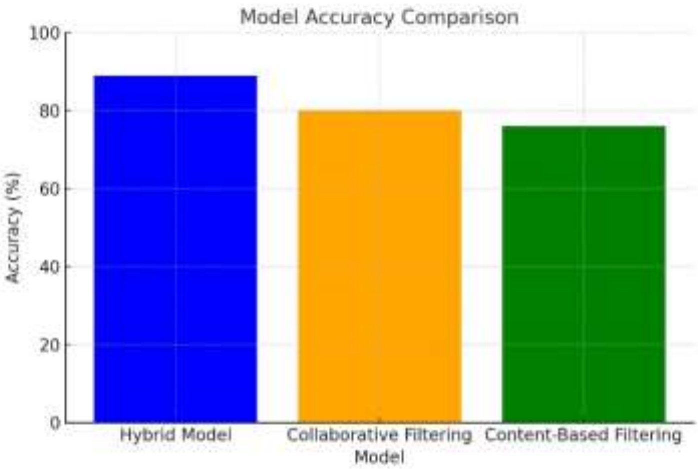


Fig 2. Accuracy Comparison of Recommendation Models

Figure 3 depicts the precision-recall trade-off for the Hybrid Model, highlighting its effectiveness in balancing these key metrics.

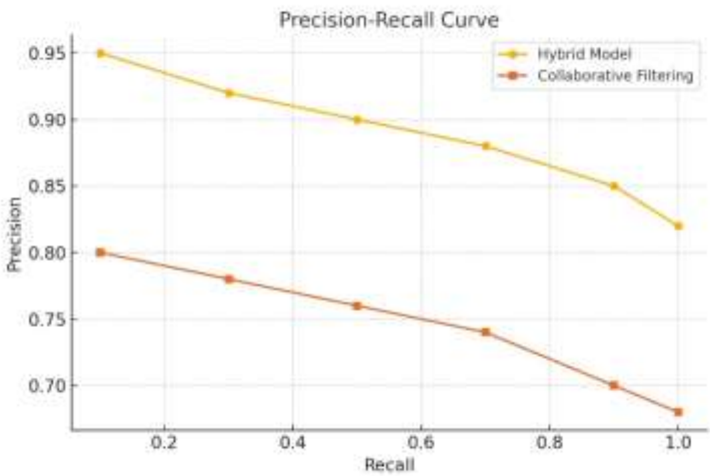


Fig 3. Precision-Recall Curve

## 6. Conclusion

This research presents a comprehensive machine learning-driven matrimonial platform tailored to enhance user matchmaking experiences. The system leverages advanced algorithms to classify user preferences, predict compatibility, and recommend potential matches with a high degree of accuracy. By integrating features such as real-time compatibility scoring, dynamic profile matching, and regional preferences, the platform offers a personalized and user-friendly interface. This approach simplifies the traditionally cumbersome process of finding suitable matches while maintaining inclusivity and scalability. The development of an intuitive web application ensures accessibility and ease of use, empowering users to make informed decisions efficiently. The platform's ability to adapt to diverse cultural and social contexts highlights its potential to redefine the digital matrimonial landscape, providing users with reliable, data-driven matchmaking solutions.

## 7. Future Scope

The system can be further enhanced by incorporating real-time behavioural analysis, such as tracking user interactions and preferences over time, to refine matchmaking algorithms dynamically. Integration with AI-driven chatbots for initial communication could foster meaningful connections between users while reducing the time to establish compatibility. Expanding the dataset to include more diverse demographics and relationship criteria would improve the platform's inclusivity and global reach.

Future developments could also include implementing advanced data visualization tools to display compatibility metrics and relationship trends for better user insights. Additionally, ensuring enhanced data security and privacy measures, such as blockchain-based user authentication, will bolster user trust and confidence. By addressing these areas, the matrimonial platform can evolve into a robust, future-ready solution that caters to a wider audience and continually adapts to the evolving dynamics of relationships and matchmaking in the digital age.

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