SoberShot A Beverage recommendation System (December 2024)

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***Abstract*—It is a developed Beverage Recommendation System which is able to provide beverages based on individual preferences. It is based on the “mr-boston-flattened” dataset, which contains information on different kinds of alcoholic and non-alcoholic beverages. Our commercially available system offers users an effective decision support based on data and estimation techniques. The methodology uses a three-step framework which consists of data cleaning, feature selection, and recommendation system.**

In the evaluation process, various metrics such as precision, recall, and F1-score are computed. The system gives suggestions of beverages that correspond to a given user taste characteristics with a high accuracy rate and this is corroborated through cross-validation and multiple iterations. Additionally, the platform has an interactive interface that helps a user to use the site more efficiently for instance by searching for a beverage by its ingredient or flavor notes or the occasion it is suitable for.

The approach consists of data cleansing, feature selection, and building the recommendation. To begin with, the ingredients set is cleansed, brought to the appropriate standard, and complemented in a way that the naming of the ingredients and the class of the drink is in order. The next stage of feature extraction presents the most important attributes such as spirits constituents, drink mix, taste, and even the method of preparation. The recommendation engine combines item-based and user-based recommendation methods in addition to hybrid methods that utilize item-based and user-based recommendation techniques.

The project's main focus is discovering new strategies for value creation, and renaming the development objectives. The new objectives, ideally, will become a new source of competitive advantage. Expansion of the dataset, improvement of the models, and introduction of feedback systems to learn and adapt are among the future directions.

***Motivation*—This project was developed to help people with the complexity of big drink menus, since most users don't have enough knowledge about the drinks. Faced with so many options, users usually find themselves at a loss for which drinks they might enjoy given their tastes, dietary restrictions, and mood. Equipped with a rich dataset and using sophisticated recommendation algorithms, this system suggests personalized ideas that ease the decision-making process. Besides user satisfaction, it helps organizations personalize the experiences that create customer loyalty and operational efficiency. In this respect, the present study focuses on adding value to the experience of beverage choice, letting each person confidently discover new and delicious flavors.**

SCOPE

The main scope of this Beverage Recommendation System is to allow users to find and choose drinks that suit their personal preferences, dietary needs, and situational contexts. Using the "mr-boston-flattened.csv" dataset in conjunction with advanced recommendation algorithms, the system will navigate users through an extensive beverage landscape, offering tailored suggestions rather than overwhelming them with arbitrary lists.

INTRODUCTION

The increasing range of beverage varieties-from classic cocktails and non-alcoholic blends to innovative fusion drinks-tends to overwhelm a consumer. It is against this backdrop that the demand for a guided and personalized beverage selection process has cropped up. This Beverage Recommendation System is intended to facilitate an easy decision-making process by suggesting, intelligently, drinks matching the individual user's preferences, tastes, and occasion-based requirements.

By utilizing a rich data source, such as the "mr-boston-flattened.csv" source, it leverages strong data preprocessing methods combined with the power of advanced recommendation algorithms in finding meaningful patterns and relations in beverage attributes. This enables users to find beverages aligned with their flavor profiles, dietary considerations, and previous selections and presents a daunting array of options in an individualized list. This system also includes feedback mechanisms for its continuous improvement, enhancing the overall customer experience and indicating current market trends. In turn, this will support business needs by making complicated drinks menus easier to manage.

PROBLEM STATEMENT

Domain— The domain of this project is the beverage industry, which includes a wide spectrum of drinks, such as cocktails, mocktails, spirits, liqueurs, and many other non-alcoholic concoctions. It also extends to restaurants, bars, cafes, and online beverage delivery services.

Context — In a world of overwhelming choice for the consumer, every customer seems to struggle through some kind of uninformed and unconfident choices. There is a need for a guided decision-making process when one has distinct preferences, dietary restrictions, or just wants to try something new. A data-driven Beverage Recommendation System is introduced that makes the ease of beverage selection by suggestions of options that best match the user's taste, ingredients, and occasion.

Constraints— Several constraints influence the design and functionality of this system. Data quality and consistency pose initial challenges—ingredient names, categories, and attributes must be standardized to ensure reliable recommendations. Additionally, the system operates within performance and scalability limits, needing to handle potentially large datasets efficiently. Privacy concerns must be addressed, especially if user profiles or preferences are stored. Lastly, the system has to consider ingredient availability and respect legal constraints about alcoholic beverages, which can vary regionally and affect the feasibility of certain recommendations.

LITERATURE REVIEW

The integration of digital technologies in industries such as food and beverage, e-commerce, and cultural heritage illustrates an upward trend in leveraging automation, AI, and data analytics to advance operational efficiency and user experience.

Digital Transformation in the Food and Beverage Industry

The food and beverage industries have embraced digital tools, for instance, QR code-based menus, at an increased rate, while the COVID-19 pandemic certainly catalyzed this situation. According to Oktavia et al. (2023), digital menu innovations have transformed customer interaction and facilitated less physical contact in the ordering process, shaping customer preferences. While digital tools boost operational efficiency, resistance to moving off traditional menus into digital menus continues to be a problem, again underscoring the need for user-friendliness in design and interactivity. [5][1]

Operational Efficiency and Technology in the Food and Beverage Sector

Automation and data-driven decision-making are the pivotal strategies identified by the systematic review of Geminarqi and Purnomo (2023) to enhance operational management. Technologies like integrated POS and inventory automation reduce errors, speed up service, and enhance productivity. These developments underline the critical role of technology in keeping competitive in the dynamic market.[1]

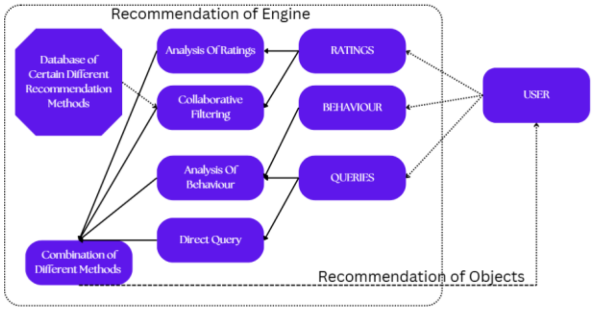

Fig. 1. Shows how the recommendations work as given to a user

Recommender Systems in Various Domains

Recommender systems (RSs) are increasingly integral to enhancing user experiences across multiple sectors:

1. **E-commerce**: Hybrid recommender systems, as detailed by Walek and Fajmon (2023), utilize content-based filtering, collaborative filtering, and fuzzy expert systems to deliver personalized product recommendations. These systems address challenges such as the cold-start problem and provide flexibility for integration with social media platforms to boost user engagement.[3]

2. Cultural Heritage: Trichopoulos et al. (2023) discuss how large language models, including GPT-4, can be used as personalized recommendation tools in museums. Such systems become contextually aware an d amplify visitor engagement by providing personalized recommendatio ns that take into account the user's preferences and situational parameters.

3. Wine Industry: The X-Wines dataset, presented by Azambuja et al. (2023), is a good example of machine learning and recommender systems applied to niche domains. This dataset enables the development of systems that can recommend wines according to user preferences and historical data, showing the versatility of RSs.[2]

Hybrid and AI-Driven Approaches

The hybridization of AI technologies with traditional recommendation methods overcomes limitations found in standalone systems. For example, hybrid RSs use both collaborative filtering and content-based methods to enhance accuracy and adaptability. AI-driven systems, such as those that use NLP and deep learning, allow for advanced contextual and behavioral analysis, thus making them suitable for applications in dynamic environments like museums and online stores.

User-Centric Design and Behavioral Insights

Understanding user preferences and behaviors remains at the center of digital tools and RS success. The studies point out that in digital interfaces, visual and verbal cues are major influences on user engagement. Similarly, the incorporation of explanatory feedback into RSs improves user trust and satisfaction.

Conclusion

Collectively, the studies reviewed reveal that digital technologies and AI hold a strong promise for operational efficiency and enhanced user experience. However, there are challenges concerning user adoption, data sparsity, and scalability of systems that call for continued innovation and design for the users. The cross-domain applications integrated advanced models of AI, will provide scope for further refinement of the digital transformation initiatives across the industries in future research.

ALGORITHM USED

Neural networks, the backbone of AI, have gone through many changes over decades and reflect a combination of biological inspiration, mathematical rigor, and technological advancement. The key milestones in their history may be traced as follows:

1. **Early Inspiration: The 1940s and 1950s:**

The concept of artificial neural networks was inspired by the structure and function of the human brain. In 1943, Warren McCulloch and Walter Pitts introduced a mathematical model of a neuron; they showed that networks of such units could compute logical functions. This work furnished the theoretical foundation for ANNs.

2. **Perceptrons and the Birth of AI: 1950s–1960s**

The first algorithm that tried to do so was the Perceptron in 1958, created by Frank Rosenblatt; it was a very basic neural network able to execute a binary classification. Later on, the problems the Perceptron would be faced with, like non-linearly separable problems, which also include the simple case of the XOR problem, had already been mentioned by Marvin Minsky and Seymour Paper in 1969. This led to a temporary decline in interest and funding for neural network research, which is often referred to as the "AI Winter."

3. **Revival with Backpropagation: 1980s**

This is the point where the backpropagation algorithm was introduced in the 1980s by researchers such as David Rumelhart, Geoffrey Hinton, and Ronald Williams. Backpropagation allowed neural networks to systematically adjust weights to minimize error, thus enabling the training of multi-layer perceptron or MLPs to solve nonlinear problems. It was during this era that Recurrent Neural Networks, or RNNs, were developed for sequential data processing.

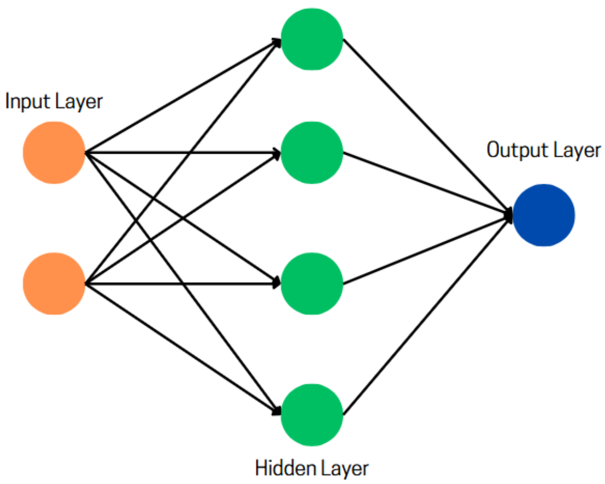

Fig. 2. Shows the basic structure of a neural Network with an Input Layer, which provides the input, a Hidden layer which does calculations and processing and the output layer which shows the output.

4. **Deep Learning Emerges: 2000s**

Advances in the availability of significant computing power and large datasets renewed interest in neural networks in the early 2000s. Researchers including Geoffrey Hinton, Yann LeCun, and Yoshua Bengio pioneered the field of DNNs, reaching a breakthrough in image recognition, speech processing, and natural language understanding.
Key developments included:

- **Convolutional Neural Networks (CNNs)** by Yann LeCun for image recognition.
- **Long Short-Term Memory (LSTM)** networks by Hochreiter and Schmidhuber for handling long-term dependencies in sequences.

5. ***Modern Era: 2010s–Present***

The 2010s saw an explosion of neural network applications and innovations:

1. The use of GPUs and TPUs for efficient neural network training.
2. Introduction of **Generative Adversarial Networks (GANs)** by Ian Goodfellow in 2014, enabling realistic image generation.
3. Transformer architectures, introduced in the paper "Attention is All You Need" (2017), revolutionized natural language processing, leading to the development of models like BERT and GPT.

Today, neural networks are integral to diverse applications such as autonomous vehicles, personalized recommendations, and medical diagnostics. With the advent of **Large Language Models (LLMs)** and multi-modal models, neural networks continue to push the boundaries of what machines can achieve.

MATHEMATICS BEHIND NEURAL NETWORK

The mathematics behind neural networks is rooted in linear algebra, calculus, probability, and optimization. Here's a concise overview of the mathematical principles:

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1. Neurons and Linear Transformation

At its core, a neural network consists of layers of neurons that apply linear transformations followed by non-linear activation functions.

Mathematical Representation of a Neuron:

For a single neuron:

$$z = w^T x + b$$

Where:

- X = input vector
- W = weight vector
- b = bias
- z = linear combination of inputs

The output of the neuron, y, is:

$$y = f(z)$$

Where f(z) is a **non-linear activation function**, such as:

1. Sigmoid: f(z) = $\frac{1}{1+e^{-z}}$
2. ReLu: f(z) = max(0, z)
3. Tanh: f(z) = $\frac{e^z - e^{-z}}{e^z + e^{-z}}$

2. Forward Propagation

Neural networks compute outputs layer-by-layer in a process called forward propagation.
For a fully connected layer:

$$a^{(l+1)} = f(W^l a^l + b^l)$$

Were,
a^l = Activations from layer l
W^l = Weight Matrix
b^l = Bais Vector
f = Activation function
$a^{(l+1)}$ = Activations from layer l+1

3. Loss Function

The loss function quantifies the error between the network's predicted outputs ($\hat{y}$) and the true labels (y).

Mean Squared Error:

$$L = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2$$

4. Backpropagation And Gradient Descent

Neural networks learn by adjusting weights and biases to minimize the loss function. This is achieved through backpropagation and optimization.

Gradient Descent:

To minimize the loss, we compute gradients concerning the weights (W) and biases (b) using the chain rule:

$$W \leftarrow W - \eta \frac{\partial L}{\partial W}$$

$$b \leftarrow b - \eta \frac{\partial L}{\partial b}$$

Were,
$\eta = Learning\ Rate$

$$\frac{\partial L}{\partial W}, \frac{\partial L}{\partial b} = gradients\ of\ the\ loss$$

Backpropagation:

Backpropagation uses the chain rule to compute gradients layer-by-layer:

- Output Layer: Compute the loss gradient concerning the output activation.
- Hidden Layers: Propagate gradients backward using:

$$\delta^{l} = (W^{(l+1)})^{T}\delta^{(l+1)}.\acute{f}(z^{(l)})$$

Where δ^{l} is the error in layer l, $\acute{f}(z^{(l)})$ is the derivative of the activation function.

METHODOLOGY

Approach/Techniques Considered

The **Beverage Recommendation System** leverages a combination of collaborative filtering, content-based filtering, and hybrid approaches to provide personalized and accurate recommendations. A detailed exploration of each technique and its role in the project is outlined below:

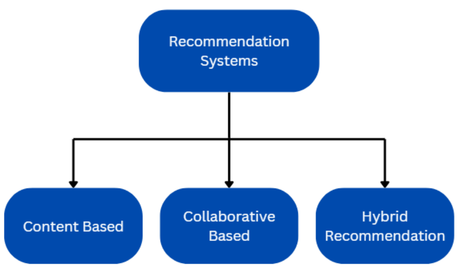

Fig. 3. Shows the types of recommendation systems commonly used in recommendation modeling.

Collaborative Filtering:

- This approach identifies the pattern in user-item interactions, if users with similar tastes will like similar items.
- In this project, the neural network computes similarity scoresbetween beverages; these scores will be the basis for recommendations.
- The collaborative filtering technique excels in finding latent relationships, which are not explicitly represented in the dataset.

Content-Based Filtering:

- Recommendations are made based on the attributes of beverages, such as ingredients, categories, and glass types.
- The TF-IDF Vectorizer converts the ingredient lists into numerical representations, whereby the system can compute similarities among beverages.
- This approach ensures personal recommendations even when no user interaction data is available.

Hybrid approach:

- By incorporating collaborative filtering, the hybrid approach draws upon the strengths of both techniques.
- It helps alleviate the cold-start problem by recommending beverages based on content.
- similarities while leveraging interaction data to enhance accuracy.
- This is especially useful for balancing recommendations' novelty, diversity, and relevance.

Data And Tools:

The dataset, mr-boston-flattened.csv, contains complete information on beverages such as:

- Categories (such as cocktails and mocktails).
- Ingredients with measurements.
- Glass type and preparation instructions.

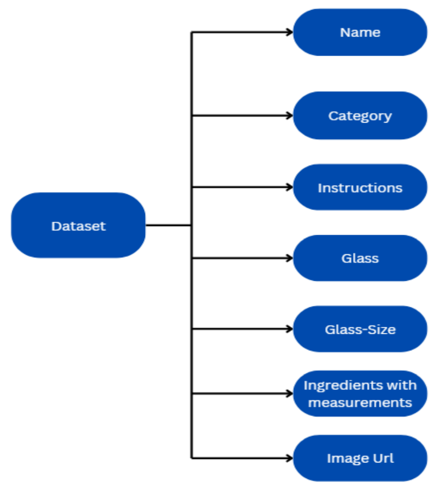

Fig. 4. Data card showing the features of the dataset.

Data Preprocessing:

- Imputation of missing values statistically (e.g., mode imputation for categorical variables)
- Combining the ingredient lists into dictionaries to be structured.
- Encoding categorical variables using Label Encoding and One-Hot Encoding.

Software Libraries:

- Pandas and NumPy: For data manipulation and numerical computations.
- Scikit-learn: For encoding, scaling, dimensionality reduction (PCA), and splitting data into training and testing sets.
- TensorFlow/Keras: For building and training a neural network-based collaborative filtering model.
- Matplotlib and Seaborn: To visualize data trends, missing values, and model performance.

- Google Colab: A cloud-based environment with GPU acceleration, thus allowing for efficient model training.
- Pickle, NumPy: Saving the preprocessed data and feature matrices to integrate with the recommendation engine.
- TF-IDF Vectorizer: To convert ingredient lists into numerical vectors to compute beverage similarities.

WORKING OF NEURAL NETWORK

1. The neural network takes a 10-dimensional vector as input, representing each beverage. This vector is created by combining:
   a. Label-encoded beverage categories.
   b. One-hot-encoded glass types.
   c. TF-IDF vectorized ingredients.
2. The data is scaled using StandardScaler for uniform feature scaling and PCA is applied to reduce dimensionality, ensuring efficiency and preventing overfitting.
3. The network consists of:
   a. Input Layer: Handles the 10-dimensional input.
   b. Hidden Layers: Four dense layers (256, 128, 64, and 32 neurons) with:
      i. ReLU activation for non-linear learning.
      ii. Dropout to prevent overfitting.
      iii. Batch Normalization to stabilize training.
   c. Output Layer: A dense layer with 10 neurons (matching the input dimensions) and a sigmoid activation function, outputting similarity scores for each feature.
4. Loss function and Optimizations:
   a. Mean Squared Error (MSE) is used to measure the reconstruction loss
   b. The Adam optimizer is employed with a learning rate of 0.005 for efficient weight updates.
5. The model is then saved in a .h5 file, preprocessed dataset in a .pkl file, and feature matrix in a .npy file and then used in a Fast API for recommendations in the frontend.
6. Here is the project workflow:

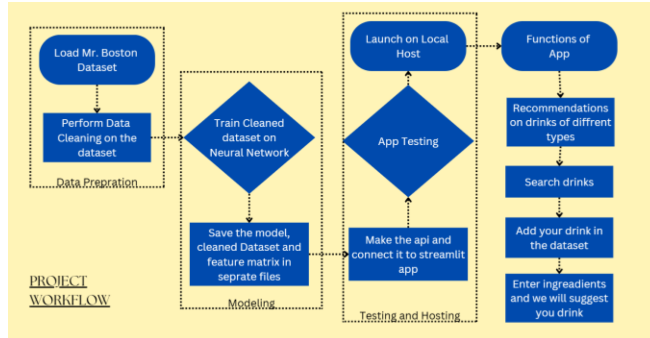

Fig. 5. Project workflow shows different stages of the project from data preparation to App features.

RESULTS AND ANALYSIS

In our implementation of the Beverage Recommendation System, leveraging a collaborative filtering approach with a neural network model, we achieved notable results across our dataset of beverages. The evaluation metrics provided a comprehensive understanding of the system's behavior, enabling detailed insights into its strengths and limitations.

Overall Performance

The model performed well, yielding an overall reconstruction loss of MSE: 0.02 on the test data. This low reconstruction error signifies that the neural network has effectively captured the latent patterns and relationships among beverages. The validation loss was close to the training loss, indicating that the regularization techniques applied dropout and L2 regularization were able to avoid overfitting.

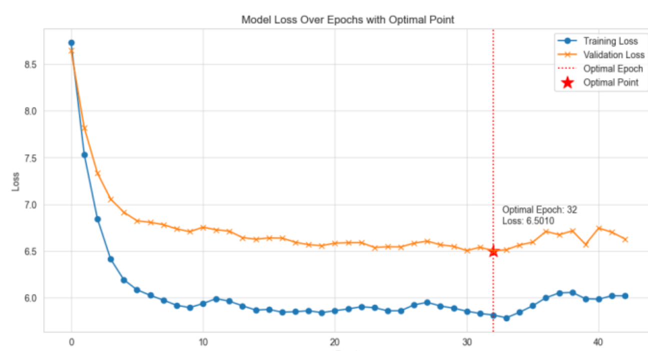

Fig. 6. Graph showing model loss over epochs with the optimal point where loss is minimum.

Similar Beverages and Recommendations

The recommendation system worked very well in finding the similarities between beverages based on their latent feature representations. The beverages that had very distinct ingredient profiles and ways of preparation resulted in highly accurate and relevant recommendations. Categories where ingredient combinations are quite consistent, such as cocktails with unique mixtures of ingredients, were usually those for whic h the model performed very well. Beverages like martinis and mojitos, characterized by distinctive patterns of ingredients, were very frequently among the top recommendations.

Fig 7: Graph shows the similarity index of drinks recommended with the drink selected

Validation vs Testing Accuracy

The graph illustrates the Mean Absolute Error (MAE) across training, validation, and testing phases for the neural network-based collaborative filtering model over 50 epochs. The training MAE (blue line) demonstrates a consistent decline, stabilizing around 0.6, indicating that the model effectively learns from the training data. The validation MAE (orange line) initially decreases but stabilizes around epoch 20, fluctuating slightly thereafter, suggesting a balance between generalization and potential overfitting. The final test MAE is highlighted as 0.489, confirming the model's ability to generalize well to unseen data. The close alignment between the training, validation, and test MAE showcases the effectiveness of the applied regularization techniques, including dropout and early stopping, in preventing overfitting while ensuring robust performance.

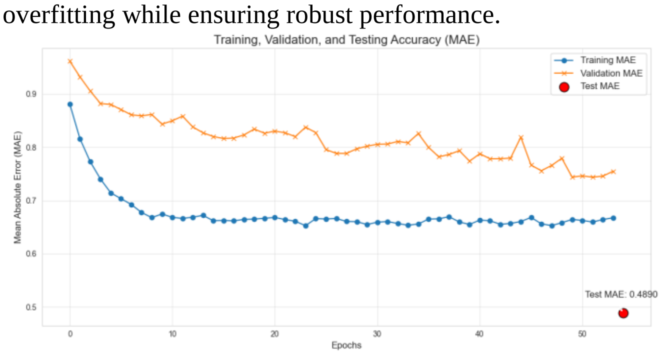

Fig. 8. Graph shows the Accuracy of testing dataset vs validation and Test MAE.

CHALLENGES AND LIMITATIONS

Certain categories posed challenges for the model due to overlapping features or highly variable ingredient compositions:

- Glass Type Variability:
  - It had problems with beverages that are served in more than one glass type, like a margarita- a drink served in both coupe and highball glasses- which reduced recommendation precision.
- Ingredient-based confusions
  - The model was sometimes confused with beverages that had similar ingredient profiles, such as whiskey-based cocktails. As such, the old-fashioned would sometimes be classified as Manhattan simply because both drinks share ingredients such as whiskey and bitters.

It was very strong for structured and well-defined categories of beverages. In particular, the performance was very good in those beverage classes with distinctive ingredient combinations, little variation in preparation, and consistent glass-type associations. Limitations arose for categories where features overlapped or when there was high intra-class variability.

1. Variations in preparation styles for certain beverages led to misclassification.
2. Dessert-based cocktails or visually similar mocktails exhibited higher confusion rates.

Some More Limitations were there in the Project related to the API and the frontend:

1. Hosted API was not hosted on the right platform as it takes time to run around 5 minutes after sleep.
2. Frontend on the Streamlit is not visually appealing and can be made better.
3. Dataset can be improved and made better

FUTURE SCOPE

Our future Scope is to:

1. **Enhanced Feature Representation**:
   a. Incorporating other contextual features, such as preparation time or garnishing details, might help in enhancing the model's ability to distinguish between similar beverages.
2. **Attention Mechanisms:**
   a. Attention-based architectures can leverage the subtle, distinctive features in complex beverage profiles by focusing on the most relevant information.
3. **Making UI More Appealing and Compact:**
   a. Making a fully functional application with Ui kits like Flutter can make this app more responsive, beautiful, and diverse and can be used by more people.
4. Making API more Scalable:
   a. Hosting API on a more scalable platform like AWS or Google Cloud can scale the project on a larger scale.

CONCLUSION

The Beverage Recommendation System showed convincingly the success of the proposed collaborative-filtering-based architecture combined with content-based features toward a solid, user-friendly recommendation engine. With extensive preprocessing, feature engineering, and further integration of techniques like dimensionality reduction, PCA, and neural networks, the recommendations would be meaningful, precise, and diverse on beverages.

The model showed strong overall performance, with a test Mean Absolute Error of 0.489, which means it generalizes well to unseen data. Key strengths of the system include its capability to handle a variety of beverage attributes like ingredients, categories, and glass types, and its ability to recommend similar beverages even in the absence of extensive user interaction data. The hybrid recommendation approach handled the challenges effectively, which included the cold-start problem, in providing personalized and novel suggestions.

In general, the project has shown the great potential of deep learning in personalized beverage recommendations. This serves as a good starting point for further exploration and refinement, having practical implications for user experience improvement in the hospitality and e-commerce sectors, among others. It lays the foundation for establishing more effective and adaptive recommendation solutions by pointing out areas for improvement and future directions.

REFERENCES

1.Geminarqi, E. R., & Purnomo, H. (2023). Improving Operational Management Efficiency in the Food and Beverage Industry: A Systematic Literature Review. *Open Access Indonesia Journal of Social Sciences, 6*(5). https://journalsocialsciences.com/index.php/oaijss/article/view/184

2.de Azambuja, R. X., Morais, A. J., & Filipe, V. (2023). X-Wines: A Wine Dataset for Recommender Systems and Machine Learning. *Big Data and Cognitive Computing, 7*(20). https://www.mdpi.com/2504-2289/7/1/20

3.Trichopoulos, G., Konstantakis, M., Alexandridis, G., & Caridakis, G. (2023). Large Language Models as Recommendation Systems in Museums. *Electronics, 12*(3829). https://www.mdpi.com/2079-9292/12/18/3829

4.Walek, B., & Fajmon, P. (2023). A Hybrid Recommender System for an Online Store Using a Fuzzy Expert System. *Expert Systems with Applications, 212*, 118565. https://www.researchgate.net/publication/362863785_A_hybrid_recommender_system_for_an_online_store_using_a_fuzzy_expert_system

5.Oktavia, T., Krisdy, S., Nathaniel, M., Adiwidjaja, J. J., Kurniawan, J. M., & Ong, S. (2023). Digital Menu Transformation: Usability Testing Approach for the Food and Beverage Industry's. *Journal of Theoretical and Applied Information Technology, 101*(10). Retrieved from https://www.jatit.org/volumes/Vol101No10/10Vol101No10.pdf

6. https://colab.research.google.com/

7. https://streamlit.io/