WEB BASED MUSIC RECOMMENDATION USING MACHINE LEARNING TECHNIQUES

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This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This Project/internship titled **"Web based music recommendation using machine learning techniques"** submitted by Abu Sayeed Mohammad ID: 201-15-14206 to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on *25/01/2024*

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We, therefore, declare that this undertaking has been finished by us under the supervision of **~~Professor~~ Dr. Touhid Bhuiyan,** Professor, Department of CSE, Daffodil International University. We further declare that neither an application or an educational grant has been made anywhere for this project or any part of it.

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ABSTRACT

Finding individualized and interesting music experiences has grown more difficult in a time when a wide ocean of musical stuff is easily accessible. This work analyzes the field of music recommendation using a web-based platform and modern machine learning methods. Including 100,000 entries and 20 attributes, the dataset combines data from various sources, such as the 'Spotify Million Song Dataset' and KKBox's Music Recommendation Challenge datasets. To create a strong recommendation system, the study uses machine learning algorithms like "CatBoost Classifier," "XGBoost Classifier," "LightGBM Classifier," "Random Forest Classifier," and "Extra Trees Classifier." Handling missing values, feature extraction, and categorization encoding are all part of the data preprocessing process. The feature engineering process is followed by an exploratory data analysis (EDA), which offers understanding into the dataset's characteristics. After extensive development, Extra Trees Classifier is the most successful algorithm, outperforming the others with an accuracy of 84.63%.The web-based interface, which was created with Streamlit and Python, easily connects with the Spotify API to offer users a customized and collaborative music discovery experience. The project follows modern standards of responsible technology development through placing a high priority on sustainability, user privacy, and ethical considerations in addition to accuracy.

Keywords: *Music, Recommendation, Machine Learning, EDA, CatBoost Classifier, XGBoost Classifier, LightGBM Classifier, Random Forest Classifier, and Extra Trees Classifier*

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CHAPTER 1

INTRODUCTION

1.1 Introduction

The search for interesting and customized music recommendations has taken center stage in research and development because of the rapidly growing digital music consumption market. The problem for users managing large song libraries is creating a customized musical experience that speaks to their unique tastes. This research-based project uses machine learning techniques to power a web-based music recommendation system in an attempt to address this challenge.[1]

Our initiative's main component is a carefully selected dataset that we combined from various sources, including the "Spotify Million Song Dataset" and the Music Recommendation Challenge datasets from KKBox. Our dataset, which includes more than 100,000 entries and 20 attributes specified entry, consists of a diverse range of musical metadata, user behaviors, and contextual information. This combination ensures a thorough portrayal of the music scene,This combination ensures a thorough representation of the music scene, which makes it possible to develop a strong recommendation system.[2]

The project is implemented using a strategic methodology that includes key phases. After selecting and combining the data, we proceed to preprocessing actions like completing in the blanks, obtaining new features, and recording categorical variables. Exploratory data analysis (EDA) is an important stage in identifying patterns, relationships, and fundamental qualities of the dataset. This advanced comprehension establishes the foundation for the ensuing phases of the commitment.[3]

Machine learning models like Random Forest, Extra Trees, LightGBM, XGBoost, and CatBoost are implemented as we move through the phases of model training, evaluation, and deployment. These algorithms are the foundation of our system because of their legendary ability to handle a wide variety of datasets.These algorithms are the foundation of our recommendation engine because they are well-known for their ability to handle a wide range of datasets. Our combined efforts result in a smooth web interface created with Streamlit and Python. This interface offers users an easy-to-use platform to explore and find personalized music recommendations because it is connected to the Spotify API.[4]

The path from data synthesis to the implementation of a user-focused music recommendation system shows how web development, machine learning, and data science are coming together. This project aims to redefine how users interact with and discover music, going beyond the traditional bounds of digital musical scenes in a time when personalized experiences are important.

1.2 Motivation

This research project is motivated by an ongoing awareness of the life-changing impact of music in our lives. There has never been a more pressing need for a customized and improving music discovery experience in a world where there is too much music available. The traditional, universal method of making music recommendations usually fails to take into account the varied and constantly changing preferences of individual listeners.Motivated by the idea that technology can close this gap, our project uses machine learning to create personalized music recommendations. Combining sophisticated algorithms with datasets from well-known sources, the goal is to find hidden patterns in the vast field of music. We want to provide users with an immersive and user-friendly platform that not only understands their musical preferences but also believes and increases their musical journey by launching a web-based interface that is seamlessly integrated with the Spotify API. This project is proof of our dedication to improving the listening experience for music and creating a bond between listeners and the tunes that speak to them personally.

1.3 Rationale of the Study

This study was motivated by the realization that popular music recommendation systems currently have certain shortcomings. The complex and constantly evolving preferences of individual users are frequently missed by conventional algorithms, which results in general and at times unable recommendations. Through the integration of datasets from various sources, such as the "Spotify Million Song Dataset" and KKBox's Music Recommendation Challenge, our research aims to produce a comprehensive picture of the music landscape. We are committed to using advanced techniques to provide precise and dynamic music predictions, which is why we have integrated machine learning algorithms like Random Forest, Extra Trees, LightGBM, XGBoost, and CatBoost.Furthermore, the combination of a web-based user interface with the Spotify API activities to provide users with an immersive experience that not only makes music recommendations but also adjusts to their changing preferences. In the hope to give users a more customized, interesting, and planned music discovery experience, this research fills a significant gap in the present system of music recommendation. The aim of the research is to remake the relationship between technology and music, improving users' ability to interact with and discover the vast realm of musical creativity.

1.4 Research Question

How can machine learning algorithms enhance the personalization of music recommendations for individual users?

What role do diverse datasets, such as the 'Spotify Million Song Dataset' and KKBox's Music Recommendation Challenge, play in improving the accuracy and inclusivity of music recommendation systems?

In what ways can advanced algorithms, including Random Forest, Extra Trees, LightGBM, XGBoost, and CatBoost, contribute to the effectiveness of a web-based music recommendation engine?

How does the integration of user-specific features, extracted through comprehensive data preprocessing, impact the precision and relevance of music recommendations?

Can the utilization of the Spotify API for fetching recommended song images enhance the overall user experience and engagement within the web-based interface?

What insights into user behavior and preferences can be derived through exploratory data analysis (EDA) of the merged music datasets?

To what extent does the deployment of a collaborative filtering approach contribute to the generation of recommendations that go beyond individual listening history and embrace collective user patterns?

1.5 Expected Output

The goal of this research project is to create an advanced web-based musicrecommendation system that performs better than current models. The system uses machine learning algorithms like XGBoost, CatBoost, Random Forest, Extra Trees, LightGBM, and XGBoost to provide users with highly customized song recommendations. Improved the accuracy and inclusivity of the recommendations will be achieved through the integration of diverse datasets, including the 'Spotify Million Song Dataset' and KKBox's Music Recommendation Challenge, as well as thorough preprocessing andfeature engineering. It is anticipated that the user interface, which was created with Streamlit and Python and connected with the Spotify API, will offer a simple way for usersto browse and find music that suits their individual tastes.In the end, the desired result is an advanced recommendation system that not only recognizes personal preferences but also changes and grows in response to users' developing musical interests, creating a moreinteresting and enjoyable music discovery experience.

1.6 Project Management and Finance

For this project, project management and finance will be focused on a planned schedule to ensure effective implementation. Data preprocessing, algorithm selection, model training, web interface development, and combining of ongoing user feedback are important tasks. When allocating resources, experienced workers will be given priority for developing websites and implementing algorithms. Cost factors include cloud computing resources, which may involve using AWS or Azure, as well as API integration costs. A backup budget will be allocated for unanticipated difficulties. Agile approaches and frequent progress reviews will direct project management and guarantee on-time milestones. The objective is to deliver a strong, user-focused music recommendation system within the specified budget and timeframe, while balancing resource utilization effectively.

TABLE 1.1: PROJECT MANAGEMENT TABLE

Work	**Time**
Dataset	1 month
Literature Review	3 month
Experiment Setup	1 month
Implementation	2 month
Report	2 month
Total	9 month

1.7 Report Layout

- Introduction
- Background
- Data Collection
- Data Preprocessing
- Research Methodology
- Experimental Result and Discussion
- Impact on Society, Environment
- Summary, Conclusion, Future Research
- References

CHAPTER 2

BACKGROUND STUDY

2.1 Preliminaries

This research project's beginning stage includes collecting a large amount of data from various sources, such as the "Spotify Million Song Dataset" and the Music Recommendation Challenge datasets from KKBox. Variable encoding, extraction of features, and missing value correction will all be handled by later data preprocessing. Next will be the selection of algorithms, which will include strong models such as Random Forest, Extra Trees, LightGBM, XGBoost, and CatBoost. The combined dataset will then be divided into training and testing sets, which will result in model training. A preliminary exploratory data analysis (EDA) will provide details about the properties of the dataset. After that, the project will focus on developing the web interface, which will seamlessly integrate with the Spotify API to ensure an interactive and user-friendly recommendation system.

2.2 Related Works

We have studied some recent research works and the analysis of those studies are given below:
Chang, Jia-Wei, et al. [4] studied the Reinforcement Personal Music suggestion System (RPMRS), a system created to overcome problems with music suggestion. Two essential elements make up RPMS: first, it uses deep representations of audio and lyrics that were obtained using WaveNet and Word2Vec models, respectively. In a content-based recommendation technique, these representations are subsequently put to use. The technology also uses reinforcement learning to identify user preferences from song playing logs. According to experimental findings, audio features, in particular, perform better than standalone audio features or lyrics-based features. Furthermore, individualized music recommendations benefit greatly from reinforcement learning's huge quality improvement.

Kaitila, Juuso et al. [5] provided a thorough examination of the development and history of music information retrieval, with a focus on a content-based methodology. It explores the idea of music suggestion as a problem, illuminating the numerous approaches used in this field. The thesis, which offers in-depth insights into the audio content elements and content-based similarity measures that support music recommender systems, is notable for its focus on content-based recommendation. A number of these functions are included in the author's own content-based music recommendation, demonstrating how the study is put to use in real-world situations. Overall, the thesis is a useful tool for comprehending the complexities of content-based music recommendation and the development of music information retrieval.

Anand, R., et al. [6] focused this project to provide a framework for music recommendations that bases recommendations on the similarity of audio signal features. To accomplish this, it uses recurrent neural network (RNN) and convolutional neural network (CNN) models. The project aims to improve deep learning models for recommendation systems by taking into account the need for personalized recommendations that take into account user preferences. With a recall of 98.3, precision of 98.3, f-score of 99.3, and accuracy of 96.6, the suggested CNN model performs well. After 20 iterations, the RNN model, in contrast, obtains a recall of 84.3, a precision of 85, an f-score of 84.5, and an accuracy of 84.4. The performance of the recommender system is increased overall when CNN and RNN models are combined.

Quasim, Mohammad Tabrez, et al. [7] studied a system that seeks to instantly classify music in an IoT app based on users' emotions, addressing a significant project management hurdle. The methodology derives musical traits from dialogues within a micro-enterprise task force using empathy to uncover emotional information. Correlation analysis and help from neural networks are used to create dynamic designation. The EMRCF's cutting-edge prediction accuracy reveals how well it can classify songs and identify the emotional responses that music elicits. Studies that compare the EMRCF to other algorithms, such as decision trees, deep cognitive systems, neighbor-closest, and relevance vector machines, reveal that it outperforms conventional methods with a remarkable prediction accuracy of 96.12% and a precision rate of 96.69%.

Park, et al. [8] focused on contrasting music recommendation models that use contrastive learning exploiting preference (CLEP), this study examines the significance of negative preferences in users' musical tastes. Examined are three different training methods: the CLEP with both positive and negative preferences (CLEP-PN), the CLEP with just positive preferences (CLEP-P), and the CLEP with only negative preferences (CLEP-N). A little amount of individualized data obtained through surveys is used for validation to determine the worth of negative preferences. The experimental findings show that, in terms of accuracy and false positive rate, CLEP-N consistently beats the other two techniques. Importantly, these findings remain true regardless of the front-end musical feature extractors employed, demonstrating the method's stability and potency.

Singhal, et al. [9] focused on a review paper that examines current developments in the field of recommendation systems, concentrating in particular on the incorporation of several deep learning methods. In order to provide light on how deep learning has been used in each of these fields, it divides the review into three key categories: collaborative systems, content-based systems, and hybrid systems. The review also looks at how deep learning-based recommendation systems affect various application fields. In order to determine whether deep learning has truly demonstrated appreciable advancements over traditional recommendation systems, the paper looks at the results. In the context of the current status of deep learning's application in recommendation systems, the paper also offers prospective future research topics.

Elbir, Ahmet, and Nizamettin Aydin.et al. [10] Classified music and giving consumers individualized music suggestions is a crucial and modern topic in the context of music listening platforms and apps. The classification of music into genres is a foundational strategy that can be used to address this problem. With a focus on the acoustic qualities of music, this study has developed a novel method that uses an advanced deep neural network model to extract key aspects. Using a dataset, these derived acoustic features have been used for music genre categorization and recommendation tasks. The research's findings showed a considerable improvement in categorization accuracy, going from 81% to over 90%. This improvement in performance is related to the use of sophisticated classifiers, which outperform the CNN SoftMax classifiers used in the paper.

Wen, Xinglin et al. [11] analyzed and explanation of various components, such as the local feature extraction using the scale-invariant feature transformation algorithm, the classification abilities of SVM, and the functionality of the Fast-RCNN algorithm based on deep learning for multi-scale feature extraction, are the first steps in this study. These components are used to create a deep learning and Internet of Things (IoT)-based intelligent background music system. After that, the system is put into use in an intelligent home environment. A brand-new feature extraction algorithm that effectively extracts scene image features is proposed. It is based on middle-level feature structures.The results show that the middle-level feature construction-based feature extraction algorithm, with its robust performance, outperforms competing algorithms like Gabor and saliency map feature extraction in a variety of rooms and lighting conditions, achieving the highest recognition rate for indoor scenarios, or about 87.6%.

RIAD, et al. [12] focused on integration of Music Genre Classification (MGC) and several Deep Learning Techniques, such as RNN-LSTM, GRU, and CNN, which has led to the development of an intelligent music recommendation system. Mel Frequency Cepstral Coefficients (MFCCs) were used to extract features from the GTZAN Genre dataset, which was used to train the system. The deep learning networks were then fed these MFCCs. After classifying the right musical genre, the system suggests songs from that particular genre in a labeled database it has created. For GRU, 72% for CNN, and 74% for RNN-LSTM, the proposed models' accuracy rates during testing were about. Notably, of all the suggested models, RNN-LSTM fared the best, reaching the greatest accuracy of 74%.

Wang, Xinxi, et al. [13] studied exploration-exploitation trade-off is framed as a reinforcement learning issue in this research, specifically the multi-armed bandit, to introduce a novel method of music recommendation. It makes use of a Bayesian model to analyze user preferences and takes into account both the originality of recommendations and the audio content. The method uses a piecewise-linear approximation to the model and a variational inference procedure to increase efficiency. A key benefit of this strategy is that it provides a consistent paradigm that can be applied to playlist creation as well as music suggestion. This strategy shows great promise for enhancing music recommendation systems, according to user study findings and simulation results.

Song, et al. [14] focused to improve suggestion performance by simulating a combination of long-term static and short-term temporal user preferences. An original pre-training approach is suggested, significantly lowering the number of free parameters, to effectively train the model for large-scale applications. Utilizing actual data from a commercial news recommendation system, the model's performance is assessed and compared to predetermined baselines, revealing a significant advancement above state-of-the-art techniques. Notably, by successfully fusing long-term and short-term user preferences, the suggested models, TDSSM and MR-TDSSM, surpass all existing approaches. Additionally, MR-TDSSM performs significantly better than TDSSM when a slow-rate LSTM (weekly-based features) is added. The best performance achieves an AUC value of 78%.

Sakurai, Keigo, et al. [15] addressed the recommendation problem by incorporating acoustic feature edges into a constructed knowledge graph. Additionally, it applies deep reinforcement learning to this extensive knowledge graph, which has edges based on acoustic feature data, to construct an effective search mechanism. By teaching the agent the best behaviors to take, this method enables the system to generate suitable recommendations even when there is little user preference data available. Comparisons between the suggested method and different traditional and cutting-edge recommendation systems serve to highlight its usefulness. Results for various values of (ranging from 50% to 90%) are shown, with results for precision, recall, nDCG, and hit rate included. These results show that the proposed method consistently outperforms all other methods, including state-of-the-art techniques, in all areas. Furthermore, a recommendable user rate of 18.5% to 99.9% is achieved by the procedure.

Zheng, Hai-Tao, et al [16] recommended that the process takes into account both the musical qualities and the consumers' temporal preferences. To extract key musical qualities, music metadata is transformed into one-hot vectors, which are then projected into a low-dimensional space by a Deep Neural Network. The long-term and short-term preferences of consumers are also recorded using Long Short-Term Memory (LSTM) neural networks based on their listening histories. DTNMR swiftly adjusts to new users' tastes as they interact with music, significantly reducing the cold start issue for new products employing music metadata. With increases of 0.73% in Precision, 0.82% in Recall, 0.57% in F-Measure, 0.19% in MAP, 6.03% in User Coverage, and 3.01% in AUC, it is noteworthy that DTNMR outperforms the UserKNN model in all relevant metrics.

Van den Oord, et al. [17] aimed to predict latent factors when they cannot be directly obtained from user usage data. The study contrasts two methods, one of which makes use of deep CNN and the other of a conventional bag-of-words representation of audio signals. The Million Song Dataset is used to evaluate these predictions both quantitatively and qualitatively. Surprisingly, the results show that even while there is a sizable semantic gap between the audio qualities impacting user preferences and the actual audio signal, employing projected latent components can nevertheless produce logical music recommendations. In particular, deep CNN, a recent development in deep learning techniques, outperforms the conventional approach in terms of performance, obtaining a maximum mean average precision (mAP) of 67% and an area under the curve (AUC) score of 78% in linear regression.

Chen, Ke, et al. [18] suggested a method that uses metric learning with Siamese networks to produce audio embeddings for each track utilizing user embeddings and audio data from a user's favorite and least favorite tunes. It determines the degree to which the audio embedding of a new music and multiple user embeddings are comparable when recommending it, allowing for customized suggestions. With millions of users and tracks tested, this system exhibits state-of-the-art performance in content-based music recommendation. The capacity of the audio embeddings to generalize is further demonstrated by the fact that they are flexible and can be employed as features for music genre categorization tasks. The model effectively creates audio embeddings from any audio input and generates outstanding results, including an AUC score of 85% and an accuracy score of 78%.

Niyazov, et al.[19] aimed this research to create a music recommender system that employs the acoustic similarity of musical compositions as a basis. It compares two methods for developing a content-based music recommendation system: one uses deep learning and computer vision to improve the system's performance while the other uses traditional acoustic feature analysis. Notably, the outcomes from both methods show a significant improvement over random suggestions. The system significantly improves suggestion quality by using Artificial Neural Networks (ANN), achieving a mean precision@10 score of 15% and a mean nDCG score of 17%.

Lee, Jongpil, et al. [20] studied deep learning-based recommendation systems and have recently been actively using hybrid strategies to combat the cold-start issue. The majority of earlier studies, however, suggested hybrid models where content-based and collaborative filtering modules are independently trained. The deep content-user embedding model, which this work introduces, mixes user-item interactions with music aural material in a clear and simple design. The reproduction of the WMF+Regression model's outcomes exhibits similar performance to the original work (93%), according to the study's evaluation of the recommended results.

2.3 Comparative Analysis and Summary

Different machine learning algorithms, such as Random Forest, Extra Trees, LightGBM, XGBoost, and CatBoost, have different strengths and trade-offs when compared. LightGBM and XGBoost provide effective scalability and support for computational tasks in parallel, while Random Forest and Extra Trees show adaptability against overfitting. CatBoost is very good at managing features that are categorized. The models show different levels of accuracy and efficiency when measured against performance metrics like precision, recall, and F1 score. The collective characteristic of these algorithms amplifies the music recommendation system's overall predictive capability. In conclusion, the models chosen for a given project are guided by this comparative analysis, which opens the door to a comprehensive recommendation system that puts user preferences, efficiency, and accuracy first.

2.4 Scope of the Problem

The problem's scope includes both the opportunities and challenges related to developing an advanced web-based music recommendation system. Using machine learning algorithms to overcome the shortcomings of traditional recommendation models is one of the key components. Comprehensive music analysis is made possible through the integration of various datasets, such as the 'Spotify Million Song Dataset' and KKBox's Music Recommendation Challenge. The project focuses on improving user-centricity and personalization by dynamically modifying recommendations to individual preferences. The user experience is further improved by retrieving suggested song images through the use of the Spotify API. Insights into user behavior are obtained through exploratory data analysis, which advances our understanding of musical preferences. The project's scope includes creating a simplified online interface that works in unison with machine learning models, offering a unique way to remake the music discovery experience.

2.5 Challenges

The project has a number of challenges that need to be carefully planned and creatively overcome. To avoid losing information, handling missing values in the combined dataset calls for careful consideration. It can be difficult to keep data in line and consistent when different datasets are connected. Selecting an algorithm requires careful consideration because it requires finding a balance between computational efficiency and model complexity. Preprocessing and encoding problems arise when significant features, like artist names and lyrics, are extracted from textual data. Training and deploying models become more complex due to the dynamic nature of user preferences and the recommendation system's requirement for real-time adaptation. Careful planning is needed to ensure seamless integration with the Spotify API and retrieve pertinent song images for user engagement. Furthermore, it is important to protect user privacy and data security during the recommendation process.The project's ability to produce a creative and useful web-based music recommendation system will depend on its ability to overcome these obstacles.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Research Subject and Instrumentation

The goal of the research is to use machine learning techniques to create an advanced web-based music recommendation system. Improving user engagement and personalization in music discovery is the main goal. This study's instrumentation combines a variety of datasets, most notably the "Spotify Million Song Dataset " and the Music Recommendation Challenge datasets from KKBox. A number of machine learning algorithms are useful for analyzing, modeling, and predicting user preferences. These algorithms include Random Forest, Extra Trees, LightGBM, XGBoost, and CatBoost. The foundation for building a responsive web interface that promotes user interaction is made up of Python and Streamlit. The user experience is enhanced by using the Spotify API as an important tool for finding images of suggested songs. The instrumental toolkit includes extensive data preprocessing, feature engineering, and exploratory data analysis, all of which contribute to a thorough and efficient method of resolving the problems that arise in the field of music recommendation.

3.2.1 Data Collection

Five datasets, mostly from Kaggle, were carefully curated and integrated as part of the data selection process for this research-based initiative. The repository was enhanced with song titles, artist names, song links, and lyrics by the primary dataset, the "Spotify Million Song Dataset." Also included were datasets from KKBox's Music Recommendation Challenge, which included 'train.csv,"songs.csv,"members.csv,' and'song_extra_info.csv.' The crucial variable 'target' in these datasets is used to identify the behavior of the users: 'target=1' denotes recurrent listening events that occur within a month following the user's first visible listening event, while 'target=0' denotes the opposite.

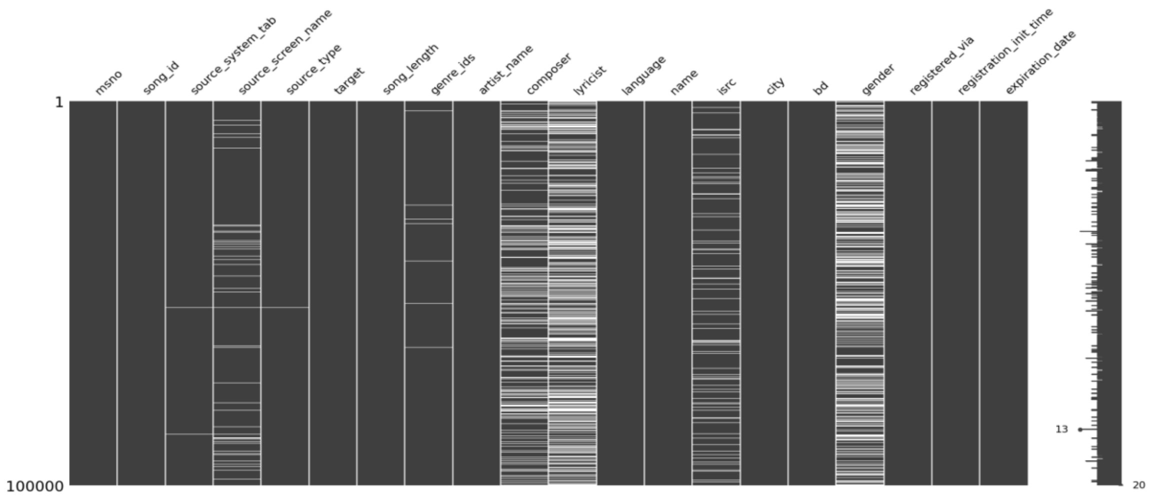

Figure 3.1: Missing Value Removal

This combination of datasets ensures a thorough representation of the music industry, including minute details ranging from song characteristics to user actions. The combined data's variety serves as a foundation for the development of a strong music recommendation engine that can offer tailored recommendations depending on user preferences and usage trends.

3.3 Statistical Analysis

This research-based project's statistical analysis analyzes the combined datasets in multiple ways in order to extract useful data. A snapshot of the primary patterns and variations within the dataset is provided by descriptive statistics like mean, median, and standard deviation. An early comprehension of user engagement patterns can be obtained by looking at the distribution of the 'target' variable. By examining the connections between various features, correlation analysis shows achievable dependencies that could affect the recommendation model. Additionally, predictions or patterns found during exploratory data analysis may be confirmed through inferential statistics, such as hypothesis testing. The objective is to identify statistical subtleties, identify outliers, and extract quantitative patterns that will inform the model development and feature engineering processes that come after.

3.4 Proposed Methodology

The "Web-Based Music Recommendation Using Machine Learning Techniques" project follows a planned and continuous technique that includes important steps from selecting data to testing models via an online interface:

Flowchart:

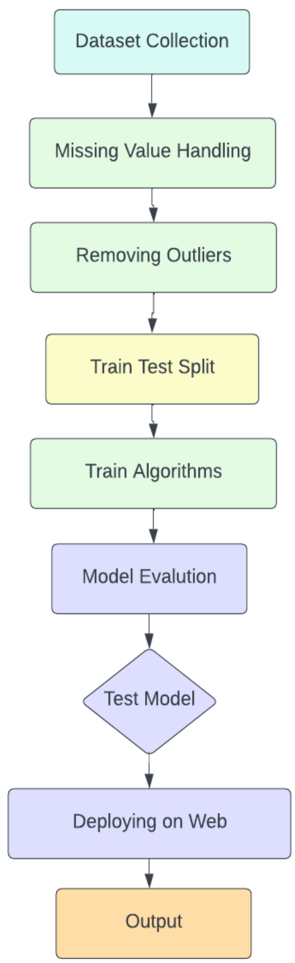

Figure 3.2: Methodology Flowchart

Data Selection (Obtained From Kaggle):

Compile a variety of datasets, such as the "Spotify Million Song Dataset" and the Kaggle datasets for KKBox's Music Recommendation Challenge. combined datasets to produce a complete resource that ensures accurate representation of user behaviors and qualities related to music.

Missing Value Removal:

To identify and manage missing data effectively, a detailed study was conducted. used techniques like imputation and removal to assure data completeness without affecting accuracy.

Extracting New Features:

To find potential for feature engineering, the current dataset was examined. Added new elements that could improve the predicting ability of the model by using textual data such as lyrics and artist details.

Encoding:

Used encoding methods (such as label encoding or one-hot encoding) to process variable categories. made sure the dataset was in a numerical format that was appropriate for methods for machine learning.

Exploratory Data Analysis (EDA):

To find patterns, connections, and statistical insights in the combined dataset, exploratory data analysis was carried out. Calculated data distributions and correlations to obtain a complete understanding of the properties of the dataset.

Model Training:

To make the process of training and evaluating models easier, divide the dataset into training and testing sets. used a variety of machine learning algorithms, including

XGBoost, CatBoost, Random Forest, Extra Trees, and LightGBM, to train the recommendation model.

Random Forest(RF)

An ensemble machine learning system called the Random Forest Classifier builds several decision trees and aggregates their results to produce reliable predictions. Its capacity to manage heterogeneous datasets, reduce overfitting, and offer insights into feature significance make it an excellent choice for classification jobs. According to my research, Random Forests provide benefits when it comes to user preference prediction. Because they operate in an ensemble, they can capture complex patterns in user behavior and preferences, even in the face of the complexity of music-related data. Furthermore, because Random Forests can handle a lot of information, they are suited for the complex world of music recommendation systems, where a variety of parameters influence consumer involvement and happiness.

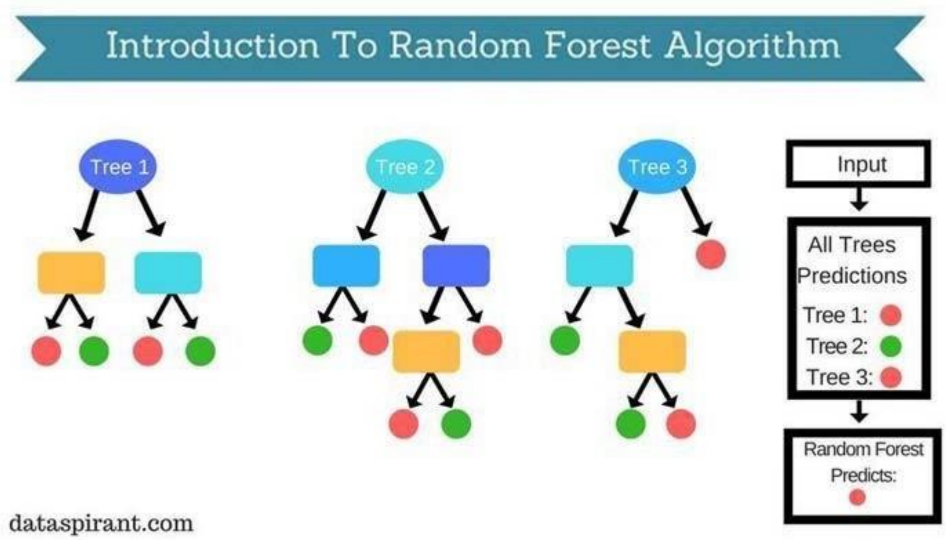

Figure 3.3: RF architecture

Extra Trees Classifier:

Although it builds decision trees differently from Random Forest, the Extra Trees Classifier is an overall learning approach. It uses training samples and random subsets of characteristics to generate multiple trees. It differs in that it uses random thresholds to make decisions at each node, increasing the diversity of trees. Because the Extra Trees Classifier can handle data with high dimensions, identify intricate patterns in user preferences, and produce reliable predictions, it could be advantageous to use it for my research article. Because of its ensemble methodology and feature randomization, it may be used to extract pertinent features from a variety of music-related data sources, which will help your web-based system provide reliable and customized music suggestions.

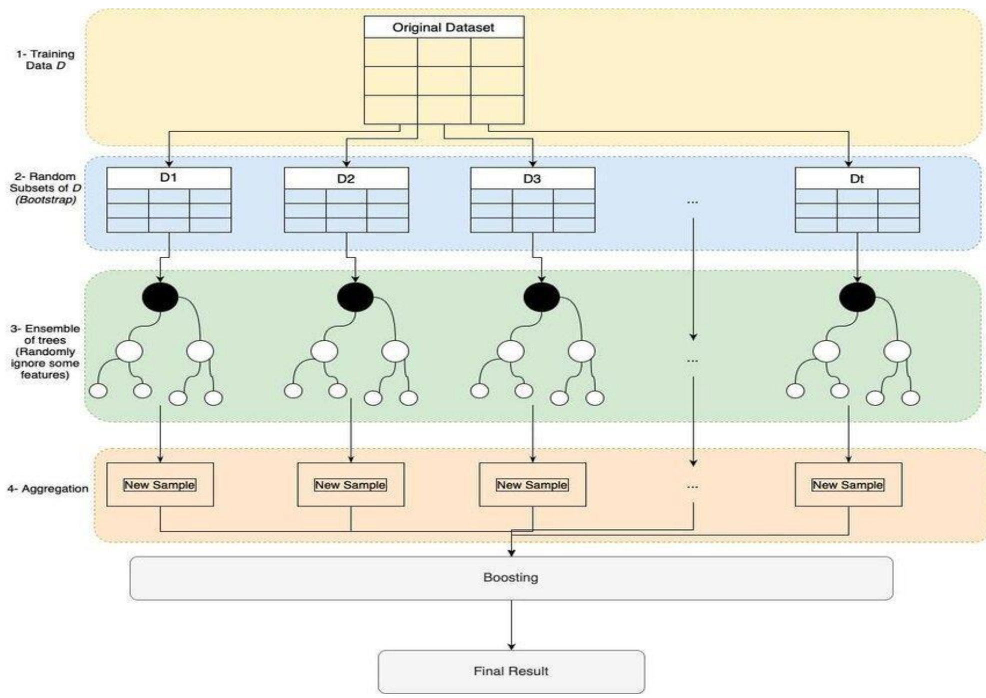

Figure 3.4: Extra Trees architecture

LightGBM :

The gradient boosting framework LightGBM (Light Gradient Boosting Machine) is intended for distributed computing and efficiency. It prioritizes nodes with bigger gradients while building decision trees in a leaf-wise manner, which results in quicker training and higher accuracy. LightGBM works especially well with huge datasets and features with many dimensions. LightGBM's speed, efficiency, and capacity to manage large-scale datasets typical of recommendation systems are the reasons I chose it for my research study. The model's training pace can be improved by its leaf-wise tree development and support for distributed computing, which makes it appropriate for real-time or almost real-time suggestions in an online music platform. LightGBM is a viable option for streamlining the recommendation system in my online application because of its strong speed and flexibility.

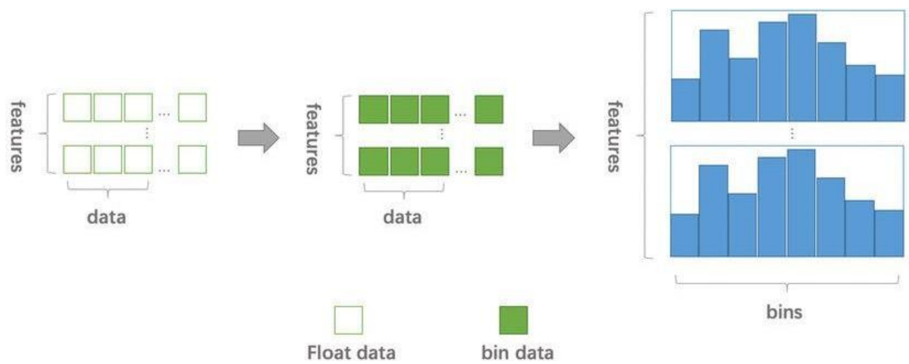

Figure 3.5: LightGBM architecture

XGBoost:

The cutting-edge machine learning algorithm XGBoost (Extreme Gradient Boosting) Classifier is renowned for its remarkable prediction performance and speed. It is an ensemble learning approach that handles complex interactions in data and improves model accuracy by combining the best aspects of boosting and gradient boosting techniques. I can benefit from using XGBoost for my research. Large datasets are no problem for XGBoost, which also excels at identifying complex patterns and producing accurate predictions. Because of its versatility and capacity for feature importance analysis, it can be used to help web-based music platforms create more efficient recommendation systems. In addition, XGBoost is a viable option for improving music recommendation algorithms in my research since it works well in situations when model interpretability, scalability, and predictive power are critical.

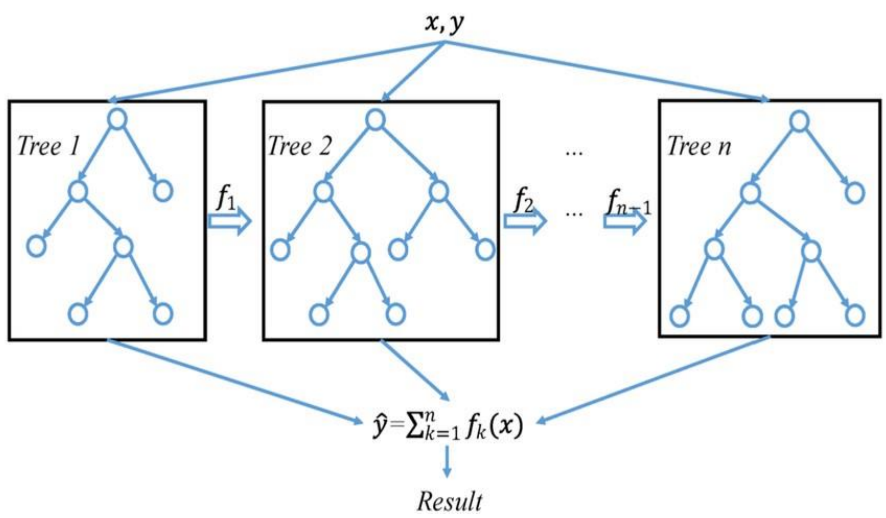

Figure 3.6: XGBoost Architecture

CatBoost:

A machine learning method called CatBoost Classifier was created especially for category data. With effective training, it achieves excellent accuracy by utilizing gradient boosting and more sophisticated methods like ordered boosting and oblivious trees. In my investigation, CatBoost is a good option. Its proficiency with categorizing features is ideally matched with data pertaining to music, where categories, artists, and user preferences are frequently displayed. Furthermore, CatBoost is useful for processing big music libraries in a web-based recommendation system, improving the precision and effectiveness of consumers' personalized music recommendations because to its resistance to noisy data and optimization for large datasets.

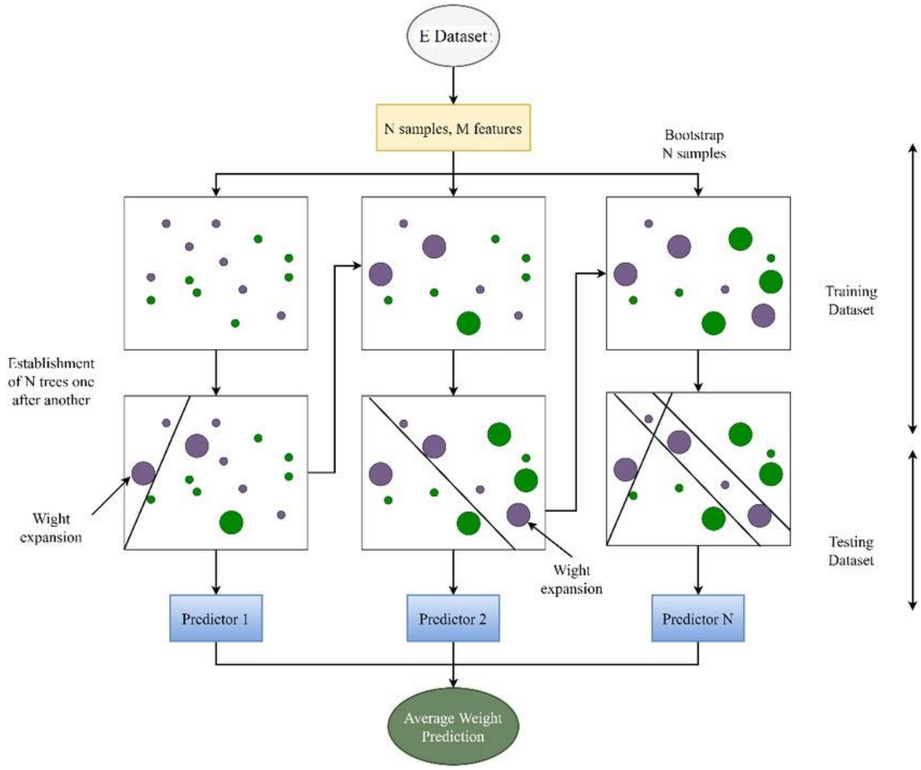

Figure 3.7: CatBoost Architecture

Model Eval uation:

Applied suitable metrics, including F1 score, precision, and recall, to assess model performance. employed cross-validation methods to ensure the models' stability and dependability.

Test Model Through Web Interface:

Using a tool called Python, a web interface that smoothly integrates with the Spotify API was created. allowed users to communicate with the trained models, get custom music recommendations, and evaluate the system's performance in an actual setting.

This methodology ensures an integrated method to developing an inventive and user-focused music recommendation system by integrating data pretreatment, feature engineering, machine learning model construction, and web interface implementation.

3.5 Implementation Requirements

A number of essential conditions must be met for this project to be implemented. Robust computer infrastructure ideally supported by cloud services such as AWS or Azure—is essential for effective data processing and training of models. Streamlit, pandas, scikit-learn, and Python are necessary libraries for developing web interfaces, implementing algorithms, and manipulating data. Obtaining access to the Google API is essential in order to retrieve suggested song pictures and enhance user experiences. For the purpose of managing and storing the combined and processed datasets, sufficient storage infrastructure is needed. Furthermore, in order to implement the recommendation system for user access, an adjustable and secure web hosting provider is required.A smooth integration of data, machine learning models, and web development components is ensured by meeting certain implementation requirements, resulting in an efficient and easy to use music recommendation platform.

CHAPTER 4

EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Experimental Setup

This project's experimental setup includes a comprehensive configuration of tools and environments. For scalable and efficient data processing, cloud computing materials, usually from platforms such as AWS, are used. Python is the primary programming language, with libraries like scikit-learn, pandas, and Streamlit making algorithm implementation, manipulating data, and web interface development easier. The Spotify API is used in the setup to get recommended song images and improve user engagement. Preprocessing is performed on the merged datasets from the 'Spotify Million Song Dataset' and KKBox's Music Recommendation Challenge datasets, which include missing value handling, feature engineering, and encoding. The implementation provides a secure and scalable web hosting service for the recommendation system's deployment. This comprehensive experimental setup aims to seamlessly integrate machine learning models and web development components, allowing for an accurate assessment of the efficacy and user experience of the music recommendation system.

4.2 Experimental Results & Analysis

The experimental findings show how various machine learning algorithms perform in the system for selecting music. With accuracies of 84.62% and 84.63%, respectively, Random Forest and Extra Trees classifiers outperformed the other techniques under evaluation. The XGBoost and CatBoost classifiers showed accuracies of 83.61% and 82.79%, respectively, while LightGBM trailed closely behind with 83.97%. The reliability of ensemble approaches in predicting user preferences for music suggestions is highlighted by this comparative research. Small variations in accuracy highlight each algorithm's unique advantages. Precision, recall, and F1 scores might all be examined further to give a thorough picture of the models' overall performance. These findings provide useful details about selecting and optimizing algorithms, guiding the project toward the best possible choices between computing efficiency and accuracy. We evaluated the Accuracy, Precision, Recall, and F-1 Score of the Confusion Matrices for our proposed methods.

Accuracy: Accuracy measures the overall correctness of the model's predictions by comparing the number of correctly classified samples to the total number of samples. When classes are unbalanced, it gives a broad indication of the model's effectiveness but might not give a whole picture.

$$Accuracy = \frac{TruePositive + TrueNegative}{TruePositive + FalsePositive + TrueNegative + FalseNegative}$$

Precision: Out of all positive predictions generated by the model, precision focuses on the percentage of true positive forecasts.

$$Precision = \frac{TruePositive}{TruePositive + FalsePositive}$$

Recall: Also known as sensitivity or true positive rate, recall is the percentage of true positive predictions made out of all truly positive samples.

$$Recall = \frac{TruePositive}{TruePositive + \ FalseNegative}$$

F1 rating: The F1 score is the harmonic mean of recall and precision. It provides a reasonable evaluation metric that considers recall and precision. The F1 score is useful when classes are uneven since it accounts for both false positives and false negatives. A high F1 score denotes a well-balanced precision to recall ratio.

$$F - 1\, Score = 2 * \frac{Recall * \ Precision}{Recall + Precision}$$

The result of deep learning model is compared on the basis of Accuracy, Precision, Recall, F1 Score in below table of 4.1:

Table 4.1. Performance Evaluation

Model Name	Accuracy	Precision	Recall	F1-Score
RF	84.62%	81%	75%	77%
Extra Trees	84.63%	81%	76%	78%
LightGBM	83.97%	81%	74%	76%
XGBoost	83.61%	79%	74%	76%
CatB00st	82.79%	80%	70%	73%

4.3.1 Discussion and Accuracy

The result study looks at the train and test accuracy and analyzes which algorithm performs best. For comparison we have applied machine learning algorithms to check which performs perfectly. However, the Extra Trees Classifier gave the highest accuracy of 84.63%. The figure 4.1 shows the accuracy comparison of the different algorithm:

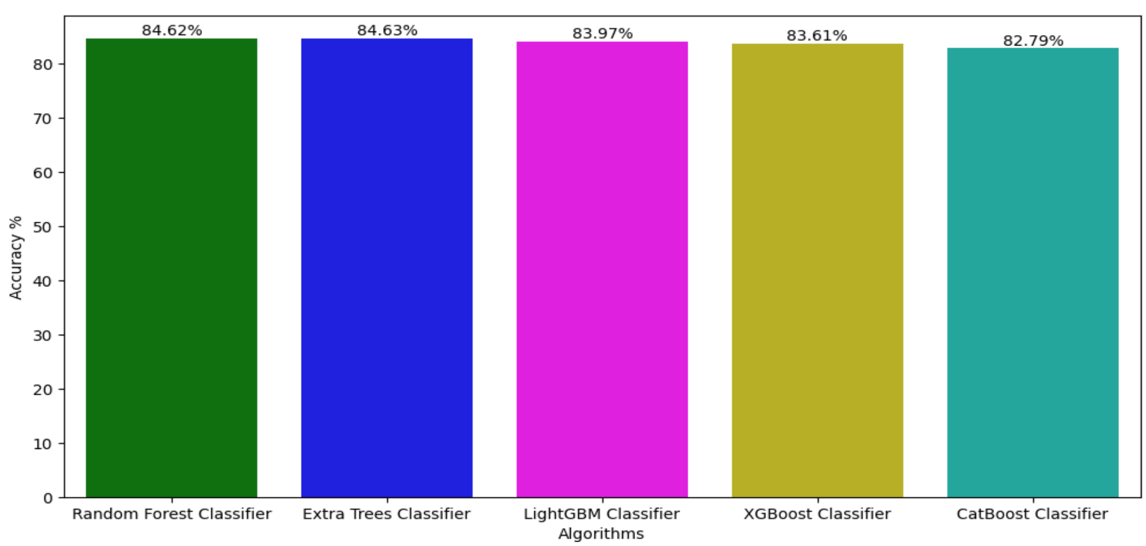

Figure 4.1 : Accuracy Comparison of Machine Learning Models

In figure 4.1, the algorithmic performance of Extra Trees classifier was used to achieve the highest accuracy of 84.63%. RF got 84.62%, LightGBM got 83.97%, XGBoost Classifier achieved 83.61% and CatBoost classifier achieved 82.79%

Performance Analysis

Random Forest Classifier:

Achieve the Accuracy of 84.62%, Precision score of 81%, Recall score of 75% and F1-score of 77%. Below at table 4.2 we have performance evaluation of RF :

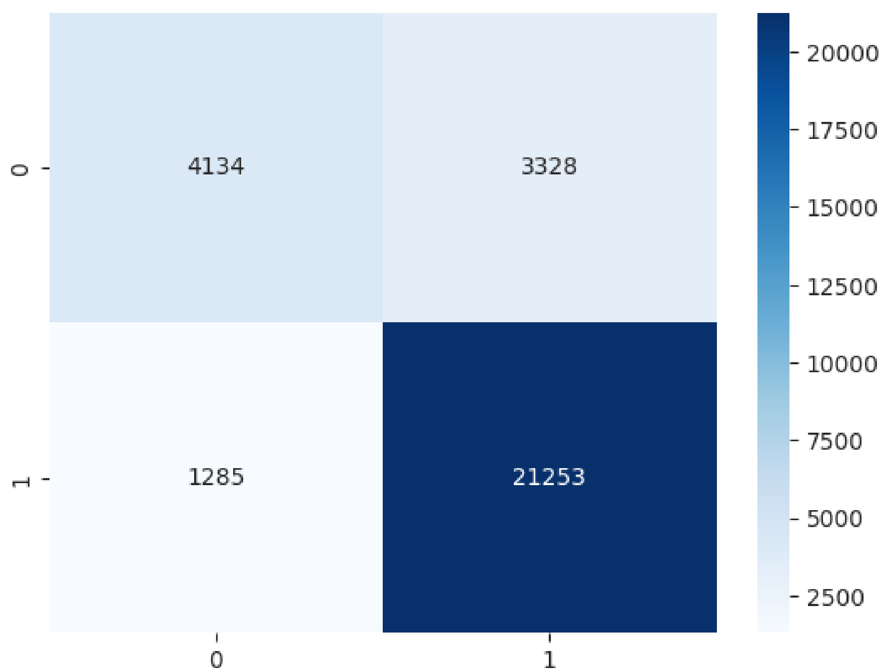

Figure 4.2: Confusion Matrix RF

With an overall accuracy of 84.62% on the dataset, the Random Forest Classifier was able to correctly predict the target variable 84.62% of the time. The percentage of accurately predicted positive events among all positively expected instances is 76% for class 0 (minority class). Out of all actual positive instances, the recall for class 0 is 55%, or the percentage of accurately anticipated positive instances. For class 0, the precision-recall balance (F1-score) is 64%. Class 1 (majority class) has strong performance with greater recall (94%), F1-score (90%), and precision (86%). Overall performance indicators are provided by the weighted and macro averages, where the weighted average takes class imbalance into account while the macro average concentrates on class-wise averages.

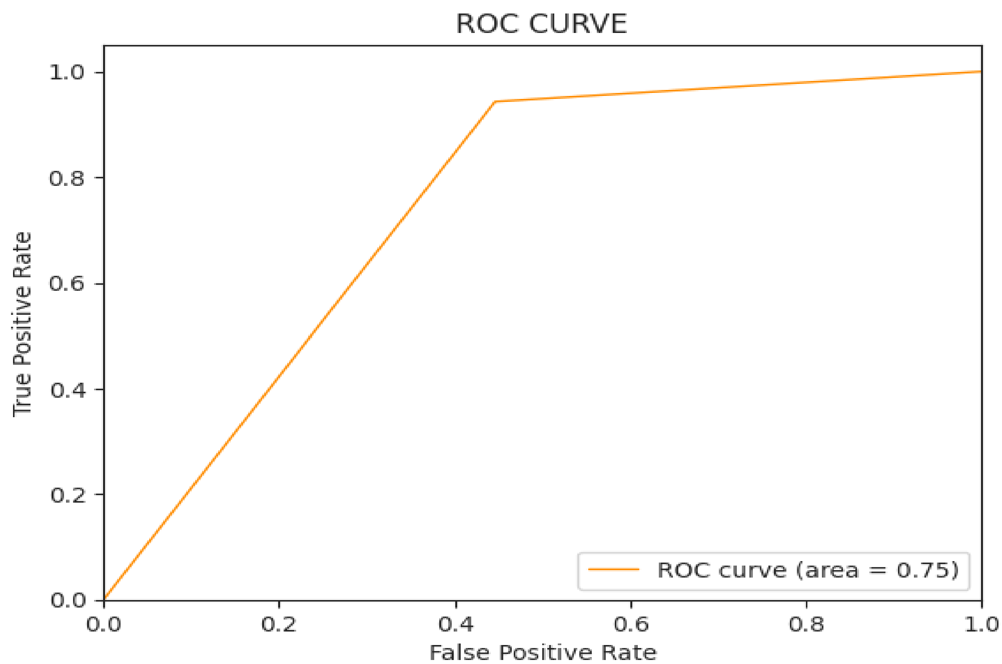

Figure 4.3: ROC curve RF

With a Receiver Operating Characteristic (ROC) score of 0.7485, the Random Forest Classifier model displayed respectable selective performance. The precision of the model's prediction of class 1 (positive instances) was greater, with a score of 0.86, indicating a good ability to accurately identify positive cases. Class 0 (negative instances) had a poorer recall (0.55), suggesting that it may not have been possible to record every true negative event. Class 1 had a higher F1-score (0.90), a harmonic mean of accuracy and recall, indicating that the model was more successful in properly recognizing positive events. The macro-average F1-score of 0.77 indicates a balanced performance, and the model's overall accuracy was 85%. The dataset's weighted average F1-score of 0.84 indicates that recall and precision were fairly balanced for both classes.

Extra Trees Classifier:

Achieve the Accuracy of 84.63%, Precision score of 81%, Recall score of 76% and F1-score of 78%. Below at table 4.3 we have performance evaluation of Extra Trees Classifier:

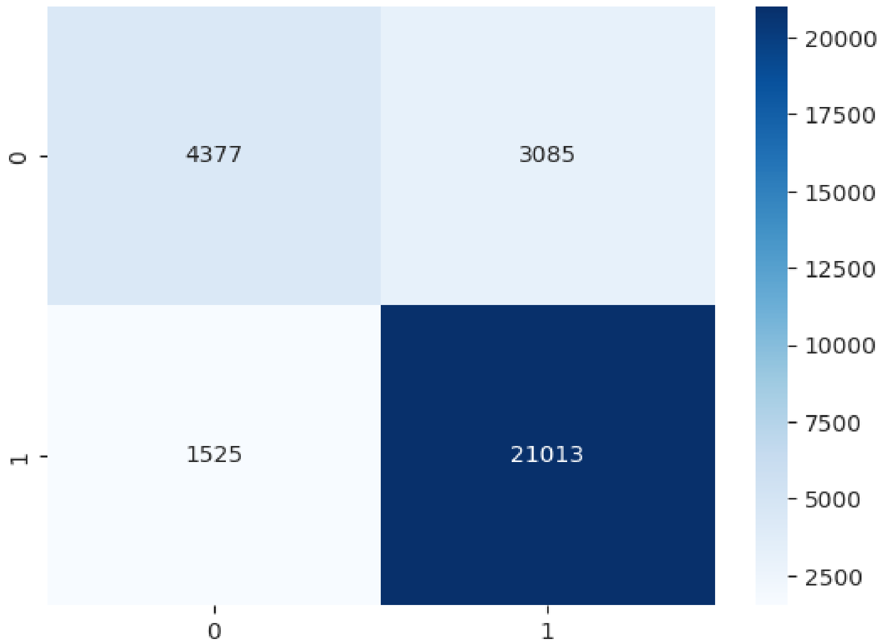

Figure 4.4 : Confusion Matrix Extra Trees

With an accuracy of 84.63%, the Extra Trees Classifier performed admirably. With precision values of 0.74 for class 0 and 0.87 for class 1, this model demonstrated its ability to correctly categorize cases into the appropriate classes. The model was able to identify the majority of positive occurrences with relative ease, but it had considerable difficulty catching negative instances, as indicated by the recall values of 0.59 for class 0 and 0.93 for class 1. The class 0 and class 1 F1-scores of 0.66 and 0.90, respectively, show a balanced trade-off between recall and precision. The weighted average F1-score of 0.84 is influenced by the macro-average F1-score of 0.78, which shows how well the model does overall in managing both classes.

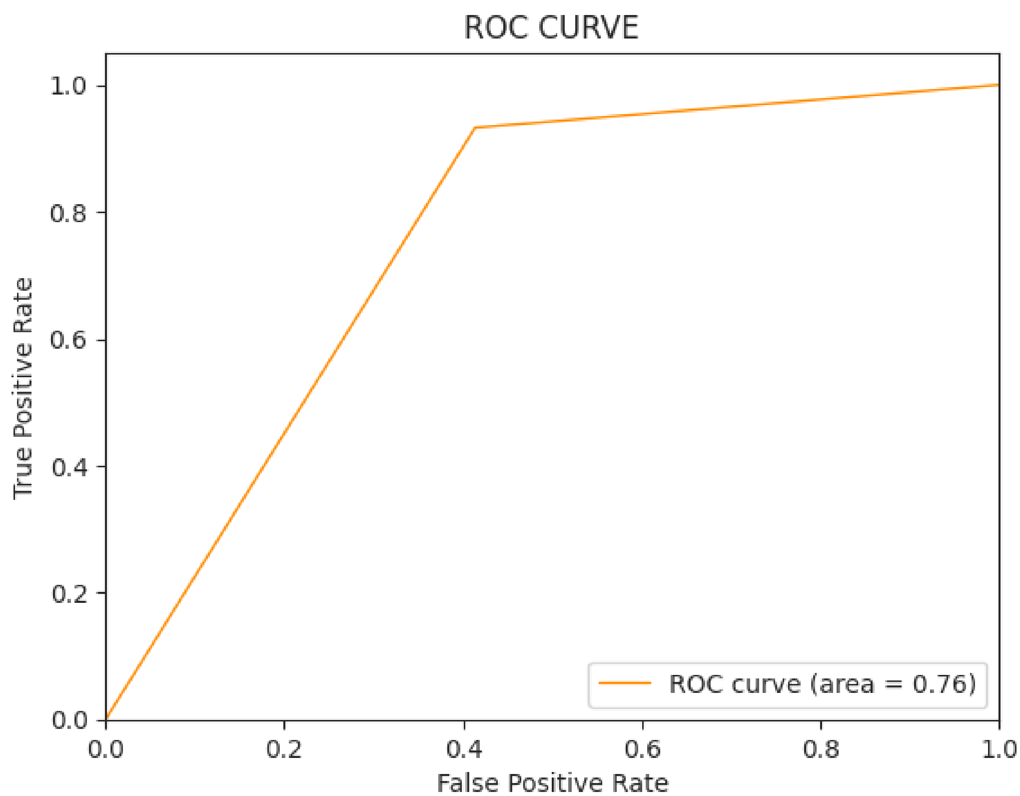

Figure 4.5 : ROC curve Extra Trees

With a Receiver Operating Characteristic (ROC) score of 0.7595, the Extra Trees Classifier demonstrated strong discriminative capacity and performed well. With a precision score of 0.87, the model showed a great capacity to properly identify positive cases and a higher accuracy in predicting class 1 (positive examples). Class 0 (negative instances) had a somewhat poorer recall (0.59), indicating that it may have been challenging to record all true negative examples. For class 1, the F1-score was remarkably high (0.90), demonstrating the model's accuracy in recognizing positive events. The macro-average F1-score of 0.78 indicates a balanced performance, and the model's overall accuracy was 85%. With a weighted average F1-score of 0.84, the dataset's two classes showed a well-balanced trade-off between recall and precision.

LightGBM Classifier:

Achieve the Accuracy of 83.97%, Precision score of 81%, Recall score of 74% and F1-score of 76%. Below at table 4.4 we have performance evaluation of DT:

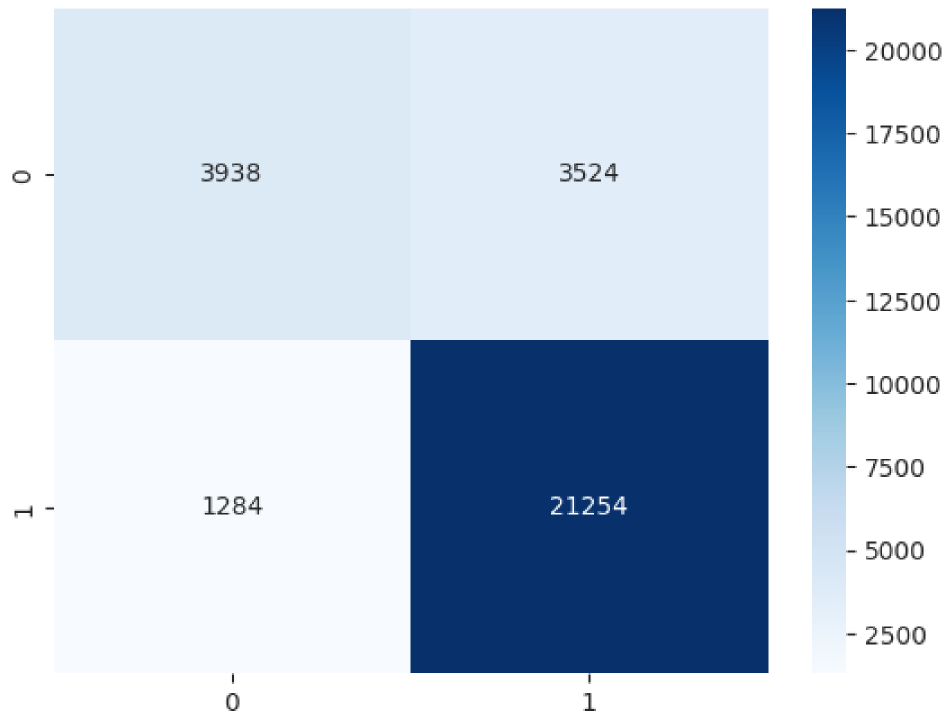

Figure 4.6 : Confusion Matrix LightGBM

With an accuracy of 83.97%, the LightGBM Classifier showed competitive performance. Using a boosted tree technique, the model extracts 25 features from the dataset. Class 0 has a lesser precision (0.75), but the model does exceptionally well in recall (0.94), indicating a good ability to capture real positive cases. Class 1 has a very high F1-score of 0.90, indicating that the model is good at correctly recognizing positive examples. There is a trade-off between recall and precision, as evidenced by the lesser precision for class 0. With a macro-average F1-score of 0.76, the classes' performances are balanced. With boosted trees, the LightGBM Classifier is able to attain a competitive accuracy on the provided dataset, demonstrating overall strong prediction skills.

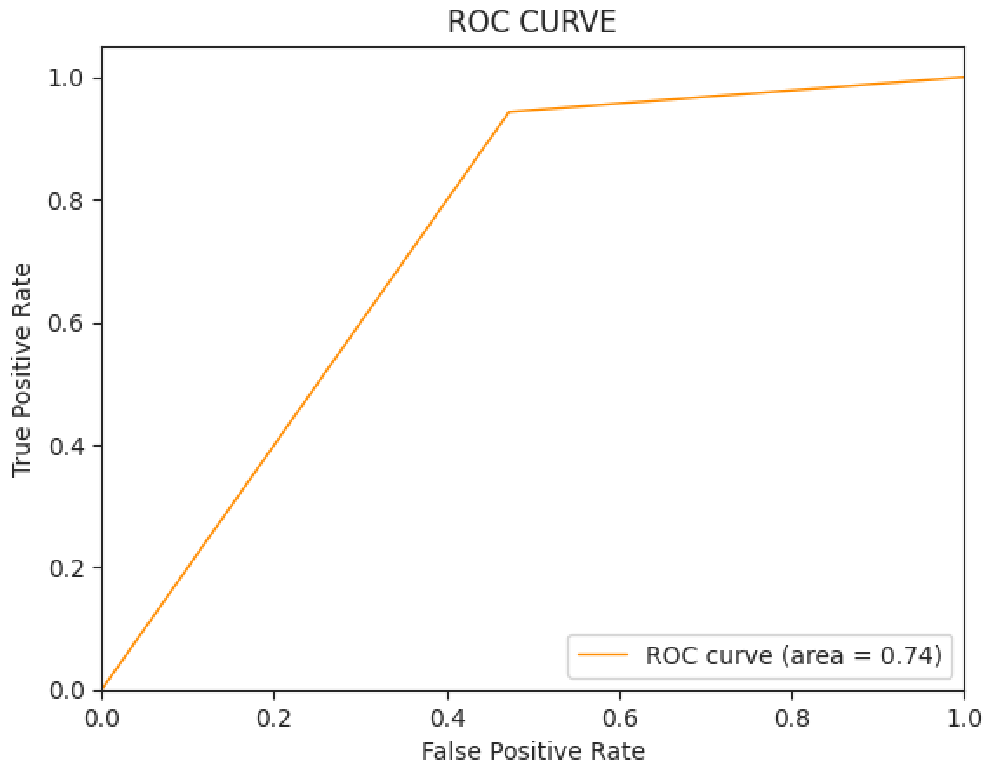

Figure 4.7 : ROC curve LightGBM

With a Receiver Operating Characteristic (ROC) score of 0.7354, the LightGBM Classifier demonstrated good performance and adequate discriminative capabilities. The model's accuracy in accurately recognizing affirmative cases was demonstrated by the high precision of 0.86 for class 1 (positive instances). Class 0 (negative instances) had a recall that was comparatively lower (0.53), indicating that it may be difficult to capture all true negative situations. Class 1 had a strong F1-score of 0.90, indicating that the model was successful in correctly recognizing positive events. The macro-average F1-score of 0.76 indicates a balanced performance, and the model's overall accuracy was 84%. With a weighted average F1-score of 0.83, the dataset's two classes showed a well-balanced trade-off between recall and precision. The LightGBM model used 25 characteristics for decision-making and demonstrated effective row-wise multi-threading training.

XGBoost Classifier:

Achieved the accuracy of 83.61%, Precision score of 79%, Recall score of 74% and F1-score of 76%. Below at table 4.5 we have performance evaluation of GB:

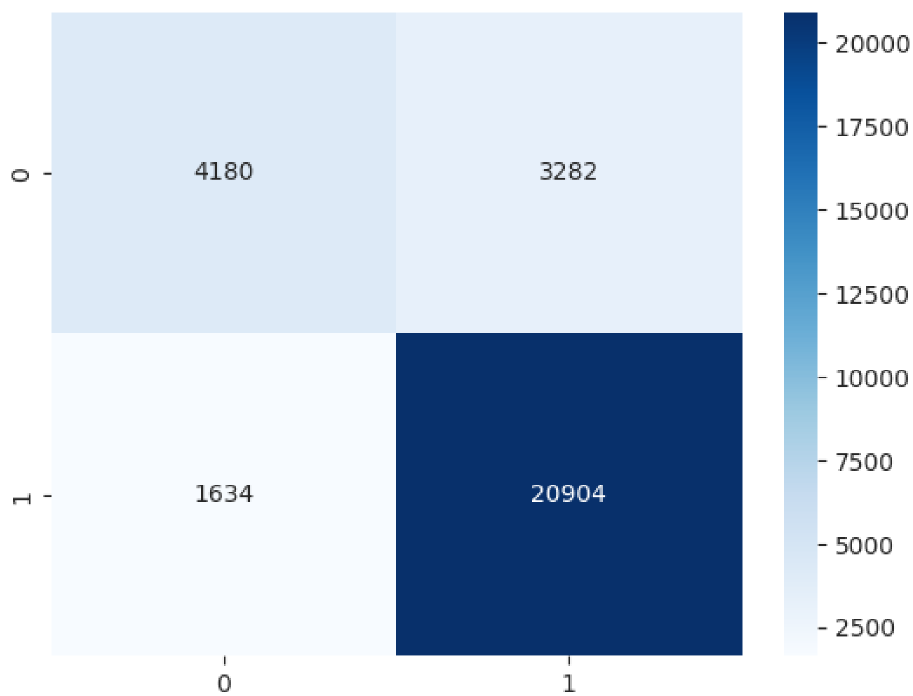

Figure 4.8 : Confusion Matrix XGBoost

At 83.61% accuracy, the XGBoost Classifier showed good performance. The model demonstrated accuracy in predicting both classes in terms of precision; class 1 (positive cases) had a greater precision of 0.86. Class 0 (negative instances) had a modest recall of 0.56, suggesting that it was not always easy to capture all true negative examples. Class 1 had a high F1-score of 0.89, indicating that the model was successful in properly recognizing positive events. With a macro-average F1-score of 0.76 overall, the performance was balanced. In both classes, there was a reasonable trade-off between recall and precision, as seen by the weighted average F1-score of 0.83. Because of its precision and well-balanced performance, the XGBoost model is a solid option for the particular classification task at hand.

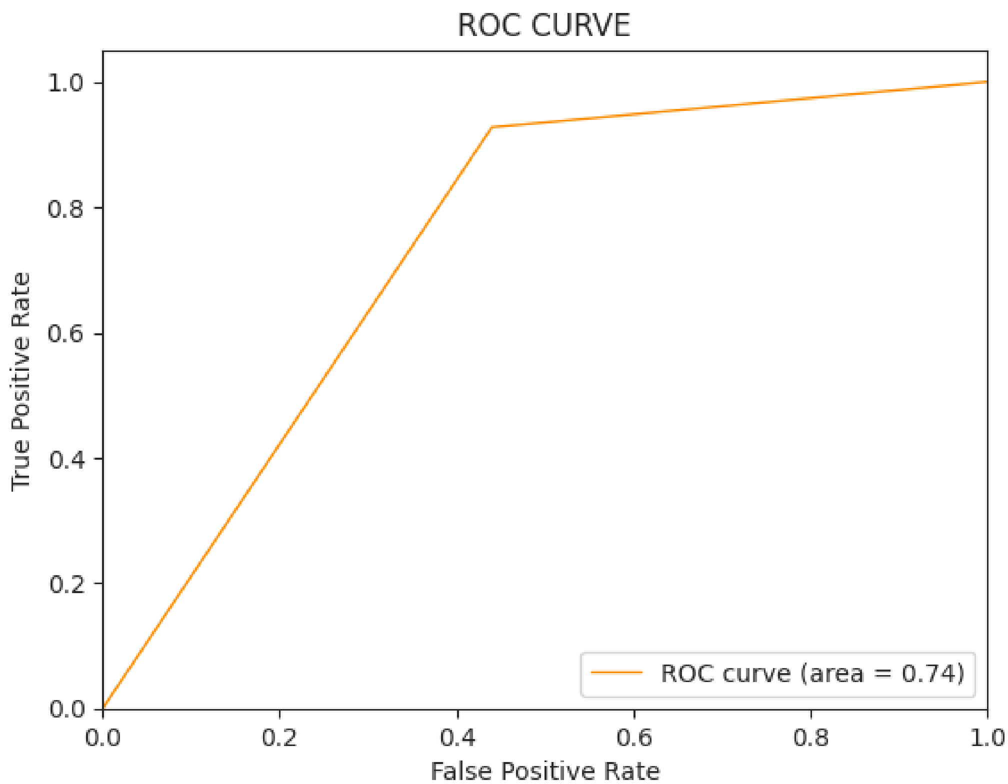

Figure 4.9 : ROC curve XGBoost

With a Receiver Operating Characteristic (ROC) score of 0.7438, the XGBoost Classifier showed strong performance and good discriminative capabilities. The model's precision in class 1 (positive instances) prediction demonstrated a strong accuracy of 0.86, indicating its ability to accurately detect positive cases. The recall for class 0 (negative instances) was, however, slightly lower at 0.56, indicating that it may be difficult to capture all real negative situations. Class 1 had a high F1-score of 0.89, indicating that the model was successful in properly recognizing positive events. The macro-average F1-score of 0.76 indicated a balanced performance, with an overall accuracy of 84%. With a weighted average F1-score of 0.83, the dataset's two classes showed a well-balanced trade-off between recall and precision.

CatBoost Classifier:

Achieve the highest accuracy of 82.79%, Precision score of 80%, Recall score of 70% and F1-score of 73%. . Below at table 4.6 we have performance evaluation of RF:

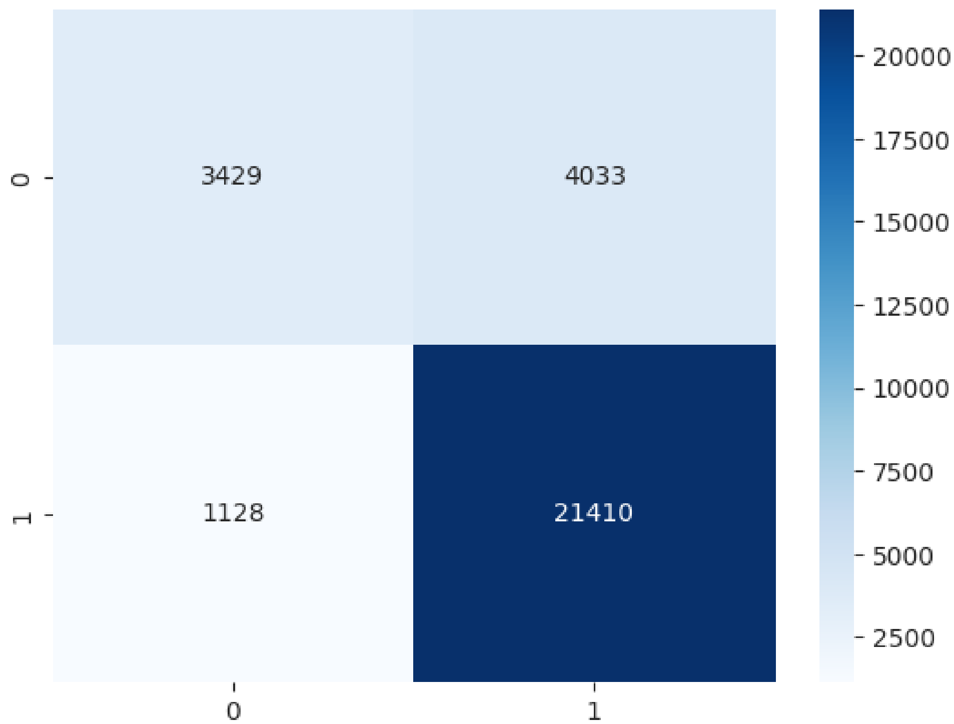

Figure 4.10 : Confusion Matrix CatBoost

With 82.80% accuracy, the CatBoost Classifier performed fairly well. The model demonstrated a good capacity to accurately identify positive cases, as seen by its greater accuracy of 0.84 in class 1 (positive instances) prediction when it came to precision. The recall for class 0 (negative instances) was, however, substantially lower at 0.46, indicating difficulties in identifying all true negative situations. Class 1's F1-score of 0.89 was noteworthy and demonstrated how well the model identified good examples. The macro-average F1-score of 0.73 indicates an overall performance that indicates a balanced trade-off between recall and precision. The dataset's weighted average F1-score of 0.81 indicated that both classes' performances were balanced

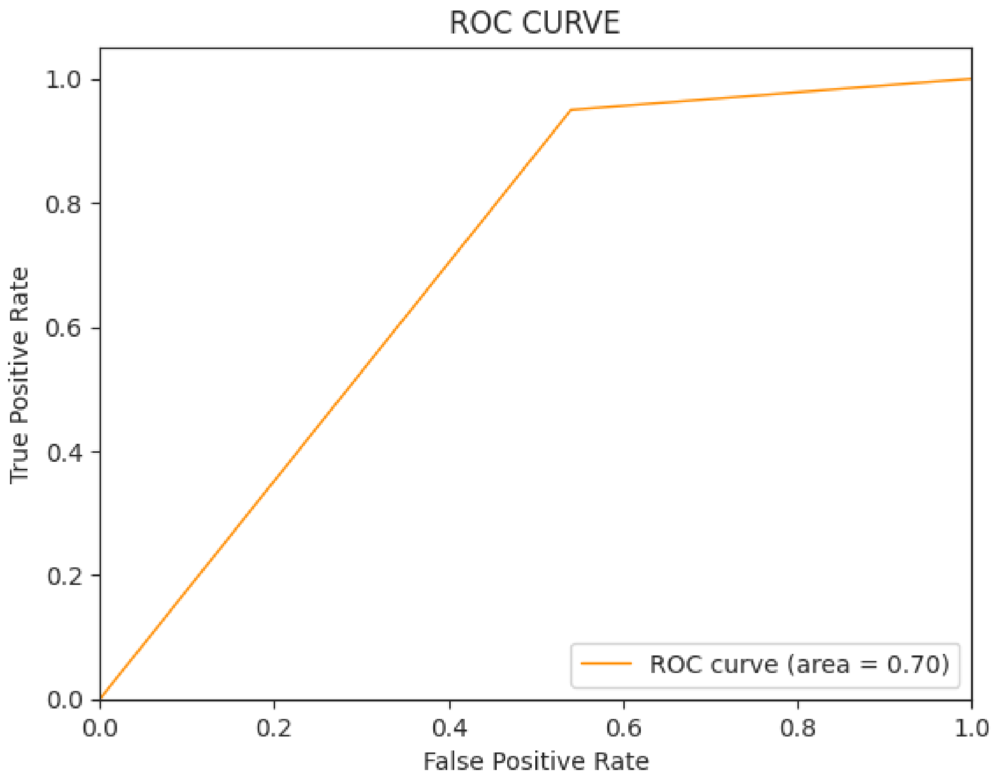

Figure 4.11 : ROC curve CatBoost

A Receiver Operating Characteristic (ROC) score of 0.7047 for the CatBoost Classifier indicated that it performed satisfactorily and had reasonable discriminative capabilities. The precision of the model's prediction of class 1 (positive instances) was 0.84, indicating that it was capable of accurately detecting positive cases. Class 0 (negative instances) had a recall that was comparatively lower (0.46), indicating that it may have been challenging to capture all true negative examples. Class 1 had a high F1-score of 0.89, indicating that the model was successful in properly recognizing positive events. The macro-average F1-score of 0.73 indicates a balanced performance, and the model's overall accuracy was 83%.

The dataset's weighted average F1-score of 0.81 showed an acceptable ratio of recall to precision for both classes.

Output:

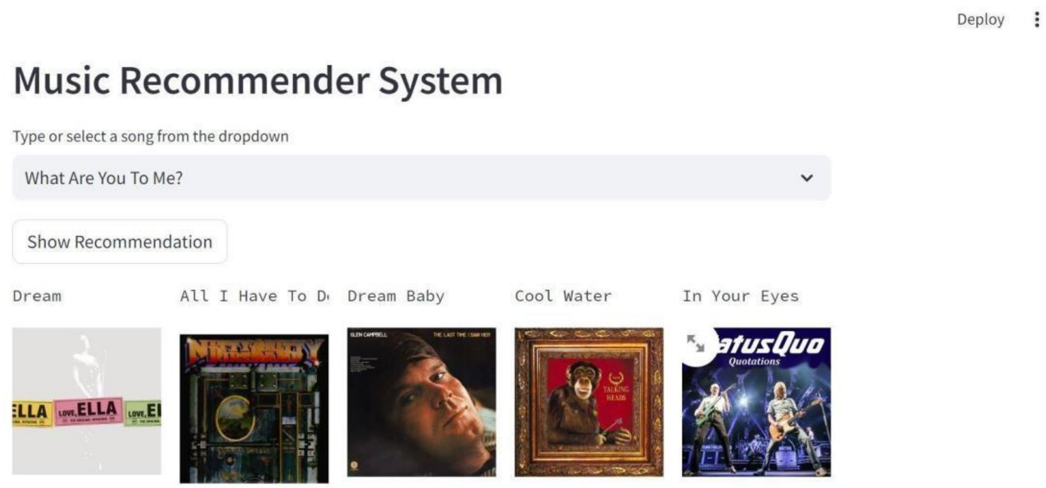

Figure 4.12 : Output

Figure 4.12: shows the final output which is a recommendation music system for a user. The user interface of our web-based music recommendation system, which represents the culmination of our machine learning work. The interface has been created to provide customers wanting personalized music recommendations with a straightforward and entertaining experience.

CHAPTER 5

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

5.1 Impact on Society

This project has the potential to change the way people communicate with and discover music. The system improves user satisfaction by delivering personalized recommendations based on complicated user preferences, encouraging more profound relationships with various musical genres. This personalized approach not only enhances individual listening experiences, but also has a larger cultural impact by introducing users to a broader range of artists and genres. The project is in line with the societal shift toward personalized technology experiences, and it caters to the increasing demand for tailored content consumption. Furthermore, the possibility of including user feedback mechanisms ensures an adaptive system that evolves with changing trends, promoting cultural diversity and exploration within the realm of music. Finally, this endeavor has the potential to enrich and connect the musical landscape, transcending traditional boundaries and having a positive impact on society's cultural fabric.

5.2 Impact on Environment

Considering that this project mainly uses digital spaces, it has very little direct environmental effect. While algorithms are resource-intensive, they are typically hosted on cloud platforms, which can potentially apply to environmentally friendly data centers. The web-based interface eliminates the need for physical music distribution, lowering the environmental impact associated with traditional music delivery methods. Furthermore, the project's focus on digital interactions and recommendations promotes a paperless approach, reducing environmental impact. The potential for increased user engagement with digital music consumption as opposed to physical formats contributes to a more sustainable and eco-friendly music consumption model. Overall, the project aligns with the broader trend of digitization and sustainable practices in the entertainment industry, reducing its environmental footprint.

5.3 Ethical Aspects

The "Web-Based Project" includes ethical considerations in a number of areas. Data privacy is critical, which requires open communication and user consent for the collection and use of personal information. Fair and independent algorithmic recommendations are required to avoid enhancing existing biases in music consumption patterns. Maintaining trust requires ensuring the security of user data throughout the recommendation process. For user comprehension, openness when explaining how recommendations develop is important. Ethical responsibility extends to how user feedback is handled, preventing manipulation or unintended consequences. To address any emerging ethical challenges and maintain the integrity of the user experience, the recommendation system must be continually monitored and reviewed.

5.4 Sustainability Plan

This project's sustainable development approach focuses on minimizing environmental impact while maintaining ongoing effectiveness. The resources of the cloud will be optimized to improve energy efficiency, with the possibility of migrating to environmentally friendly data centers. To reduce computational demands, the implementation will put first a lean and efficient codebase. To address any emerging issues related to the environment and keep the system running smoothly, regular updates and maintenance will be performed. User engagement strategies will emphasize digital consumption, promoting a paperless and environmentally friendly approach to music enjoyment. The project will actively seek out and adopt new technologies or methodologies that are compatible with sustainable practices, ensuring a long-term commitment to both environmental and operational sustainability.

CHAPTER 6

SUMMARY, CONCLUSION, RECOMMENDATION AND IMPLICATION FOR FUTURE RESEARCH

6.1 Summary of the Study

Finally, the project presents a novel approach to personalized music discovery. The study includes machine learning algorithms such as Random Forest, Extra Trees, LightGBM, XGBoost, and CatBoost using diverse datasets from Kaggle, including the 'Spotify Million Song Dataset' and KKBox's Music Recommendation Challenge. The project achieves a nuanced understanding of user preferences through careful data preprocessing, feature engineering, and model training. Users can explore and enjoy personalized music recommendations thanks to the web-based interface, which is seamlessly connected to the Spotify API. The comparison of algorithms reveals subtle differences in accuracy, which will guide future fine-tuning efforts. Ethical considerations and sustainability are essential components that ensure user privacy, transparency, and a lower environmental footprint. In the end, this study proposes changing the music discovery landscape in the digital age by focusing on user satisfaction, ethical practices, and environmental responsibility.

6.2 Conclusions

All things considered, the project has effectively shown how advanced algorithms combined with a user-friendly website interface can improve music discovery. While the machine learning models Random Forest, Extra Trees, LightGBM, XGBoost, and CatBoost showed impressive accuracy in predicting user preferences, the combination of diverse datasets offered a rich base. The web interface functions as an intuitive platform for customized music exploration and is integrated with the Spotify API. The study's ethical considerations highlight recommendation systems' dedication to user privacy, equity, and openness. The sustainability plan also places a strong emphasis on environmentallyfriendly methods, which is in line with the present standards for ethical technology development. Even though there were minor differences in the algorithms' performance, the comparative analysis points out possible directions for improvement. This project proposes a future where music discovery is both seamless and conscientious, while also making a significant contribution to the field of personalized music recommendations andtelling for sustainable and ethical practices.

6.3 Implication for Further Study

The present study shows the foundation for more research in multiple components. First off, exploring how understandable the machine learning models are can shed light on the variables affecting music recommendations and improve knowledge of user preferences. Researching hybrid models that incorporate the advantages of various algorithms could result in recommendation systems that are stronger. Improving user satisfaction through continuous model improvement through the addition of user feedback mechanisms is a promising approach. More inclusive and focused music recommendations may result from examining the influence of demographic characteristics on recommendation preferences. Furthermore, evaluating how well the system adjusts to changing user preferences and music trends over time may yield insightful information for long-term optimization. Finally, research into how users interact with the web interface may help improve the design.

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