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AN ENSEMBLE MOVIE RECOMMENDER SYSTEM BASED ON STACKING

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ABSTRACT

In the digital realm, recommender systems are information-filtering algorithms that influence consumer behavior by recommending appropriate products to users. We have proposed an ensemble movie recommender system based on the stacking technique of ensemble learning. The MovieLens dataset from the Grouplens project was used to evaluate the proposed recommender system. The primary objective of this study is to assess the effectiveness of an ensemble movie recommender system based on the stacking technique of ensemble learning. By exploring both standalone and layered models, we aim to demonstrate the potential benefits of ensemble learning in the context of movie recommendations. We have tested with a variety of base learner combinations to identify the ideal base learner and meta-learner pairing for the proposed recommender system. Regression models, including K-Nearest Neighbors and Linear Regressor, and ensemble models such as Random Forest, GradientBoost, XGBoost (eXtreme Gradient Boosting), and AdaBoost have all been tested for this purpose. According to the experiments, layered models perform better than standalone models. Additionally, it has been found that XGBoost performs exceptionally well both as a base learner and as a meta-learner in the proposed stacked model.The main aim of this paper is to increase the model's overall performance and comparison with existing works. We have tested our model using evaluation measures including mean absolute error (MAE), mean squared error (MSE), and root mean square error (RMSE). Our proposed model with 0.69 MAE, 0.81 MSE, and 0.90 RMSE is better than existing works with (0.78 MAE) [17], (0.75 MAE) [18], and (0.70 MAE, 0.83 MSE, 0.91 RMSE) [19].

Keywords: *Ensemble learning, Recommender system, Stacking, XGBoost, Classification, Regression*

1 INTRODUCTION

In the realm of today's digital entertainment landscape, the availability of an extensive array of movies poses a challenge to individuals seeking personalized viewing experiences. Recommender systems make suggestions to users about items they believe the user will find interesting based on information they have about the user.Traditional recommendation methods often fall short in providing individual preferences and diverse choices. In recent years, recommender systems have spread widely and are used in many different contexts. Movies, music, news, books, scholarly articles, search queries, social tags, and items are a few examples of common application domains for recommender systems.When a person browses through a vast catalogue of products like those at Amazon, Netflix, Spotify, or Google News, they often have no idea exactly what they're looking for. This is where recommendation engines come in. Recommender systems embedded incommercial applications provide recommendations to the customers and encourage them to buy different kinds of products of their interest such as watches, cameras, PCs, books, etc. Recommender systems have already shown tremendous utility in e-commerce sales. Casual shoppers who typically visit websites just for browsing various products and catalogs have been increasingly shopping and paying more as recommender systems have become more effective in suggesting relevant products to relevant customers. By converting casual surfers into customers, increasing cross-selling by suggesting related products, and fostering client loyalty, recommendation systems boost e-commerce sales. Commercial recommendation systems are employed by companies like Amazon, eBay, Flipkart, and others.

Previous research in the field of recommender systems has focused on information-filtering algorithms mainly that influence consumer behavior by recommending appropriate products to customers. In this regard, we present an ensemble movie recommender system that employs the stacking technique of ensemble learning. The study's primary goal is to assess the effectiveness of this ensemble system and demonstrate the benefits of ensemble learning in movie recommendations.

1.1 Types of Recommender Systems

Any recommender system can be divided into different types based on the methodology employed to design it. The simplest and most traditional sort of recommendation system is one in which site administrators make recommendations without input from website visitors. Examples of suggestions include a list of favorites, a list of necessary things, etc. Another kind of recommendation system uses user activity to suggest other users, but the recommendations are independent of the user and instead depend on the combined activity of many other users. For example, recommendations are made in the form of a list of top ten movies or videos on many websites which comes under the non-personalized or popularity-based recommendation. The most popular type of recommendation system is a personalized recommendation system, where recommendations are made based on user behavior. For example, movie recommendations based on your previously watched movies and music recommendations based on your music interests etc. Content-based, collaborative, and hybrid recommender systems are the three basic categories into which personalized recommendation systems are divided. Fig. 1 provides a diagrammatic illustration of the different categories of recommender systems.

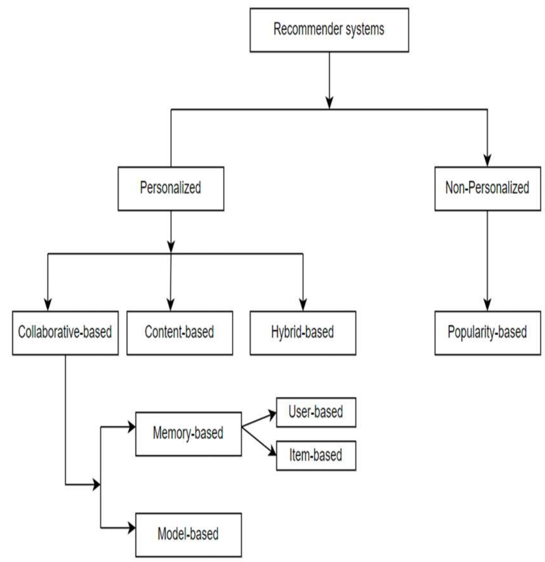

Figure 1: Types of recommender systems

1.6.1 Collaborative recommender system

A similarity metric serves as the foundation for collaborative filtering. For instance, identify the group of users N who share the preferences of user X and who disapprove of the same items as X. Next, identify other items that are popular among the group N and suggest them to user X. User to user collaboration or item to item collaboration are both possible in collaborative filtering.In user-to-user collaborative filtering, to predict the ratings given by a user for a particular item, we find the users that are similar to that user who have also rated the same item. Through item-to-item collaborative filtering, we discover other items that are comparable to item I and that have been rated by the same user. Fig. 2 provides a diagrammatic representation of the collaborative-based recommender system.

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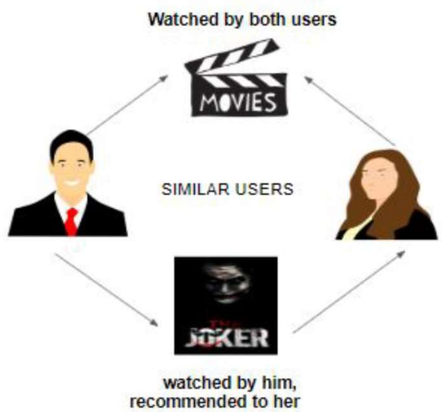

Figure 2: collaborative-based recommender systems

1.6.2 Content based recommender system

Content-based filtering methods are based on a description of the item that is rated positively by the user. For each user and item in content-based recommendations, a "profile" is built. Fig. 3 provides a diagrammatic representation of the content-based recommender system

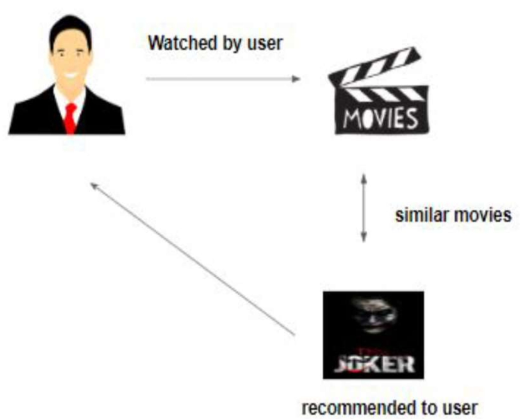

Figure3: Content-based recommender systems

1.6.3 Hybrid recommender system

On the other hand, the hybrid strategy combines two or more approaches. There are several ways to execute a hybrid strategy, including using predictions from both collaborative and content-based approaches independently before integrating them, or by adding collaborative-based approach features to a content-based approach and vice versa.

1.6.4 Ensemble Learning

Ensemble learning uses multiple learning algorithms at the same time to obtain better predictions than individual models. Ensemble learning gives us better accuracy, avoids overfitting,and also reduces bias and variance errors. Some of the popular techniques of ensemble learning are bagging, boosting, stacking, etc. In the bagging technique, subsets of a dataset are randomly selected from the training dataset and several models of the same learning algorithm are trained using the homogeneous ensemble technique. The predictions made by the individual models are aggregated to get the final prediction. Boosting combines multiple models which may or may not be homogeneous. In boosting, multiple models are trained in sequence and each model fixes the error of the previous model in the sequence. In boosting, more emphasis is given to misclassified data points to improve accuracy. Our proposed movie recommender system uses the stacking technique of ensemble learning to recommend with high accuracy.

Building recommendation systems have recently been greatly influenced by ensemble learning, which combines predictions from various separate models to get superior composite predictions [1]. According to the literature, using the ensemble method can considerably increase the performance of recommendation systems [3],[6]. An ensemble system creates a superior composite global model with more accurate and trustworthy estimates or choices by combining a number of models, each of which solves the same initial problem. In order to create a strong ensemble, the base learners should be as diverse as possible. Current research on ensemble learning demonstrates that ensemble-based approaches typically yield superior outcomes to any stand-alone algorithm. Figure 4 provides a diagrammatic illustration of the various ensemble learning technique.

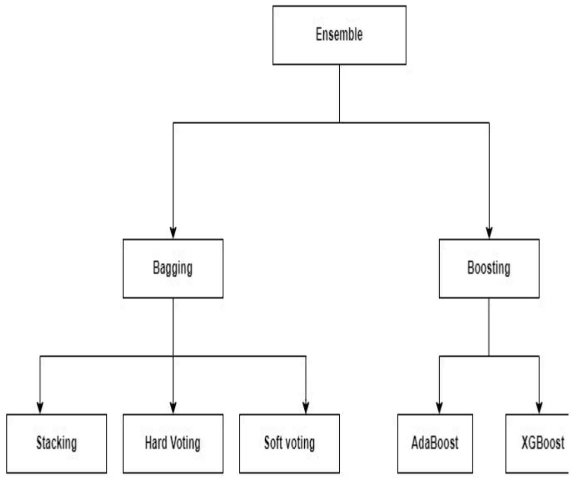

Figure 4: Types of Ensemble learning technique

In this research, we offer an effective ensemble-based movie recommender system that makes use of the ensemble learning stacking technique. The following is how the paper is set up:Section 2 presents a brief overview of related work, Section 3 describes the methods used to create our proposed model, Section 4 presents and discusses the experimental findings, and Section 5 discusses the conclusion and future work.

2 LITERATURE REVIEW

The fundamental issue addressed in our study is the necessity for an updated and comprehensive movie recommendation system that takes both accuracy and diversity into account when making recommendations. In this section, we give a review of some of the important research in the area of ensemble learning-based recommendation systems. We focused on literature published in reputable conferences, journals, and research platforms within the last few years. We searched for research papers and publications that directly addressed ensemble learning approaches, in the context of recommendation systems and we have also included papers thatcompare the efficiency of different ensemble approaches. This assured that the material we chose is relevant to the key subject of our investigation. Approaches to ensemble learning differ in two main respects, namely the individual models used and the method by which these individual models are ensembled. The stacking model also called stacked generalization was proposed by David Wolpert in 1992[2]. In a two-layer stacking model, base learners are trained in the first layer and a meta-learner is used to create a final prediction in the second layer. Zhou et al.[3] proposed an algorithm for purchase prediction usingthe stacking technique of ensemble learning. In their proposed approach, they have used multi-model stacking where they have trained four different ensemble models in the first layer, and then another ensemble model is used in the next layer to combine the predictions made in the previous layer. Li et al.[4] have done a comparative study of different ensemble techniques like bagging, boosting, and stacking with five different individual models viz. - Neural Network, Decision Tree, Logistic Regression, Naive Bayes, and Support Vector Machine. Their performance is evaluated on a credit dataset to predict credit risk and it is observed that except for AdaBoost, the other ensemble models give better results than the individual models. Dey et al. [5] have used the ensemble method XGBoost to propose a predictive model for stock market prediction and it is observed that the proposed model gives a very efficient result with an accuracy of 87%. Collaborative filtering was used to create a framework by Bar et al. [6] to examine the impact of employing ensemble techniques on various base models. Bagging, boosting, fusing, and randomness injection are the ensemble techniques that have been tested and are being compared. They have analyzed that when the ensemble approach is used with a collaborative filtering-based model, the RMSE value is decreased and the accuracy of the algorithms is increased. The usefulness of various ensemble-based classifiers, including Random Forest, XGBoost, AdaBoost, etc. in forecasting stock price movement was analyzed by Qin et al. [7]. They noted that compared to the other classifiers, the AdaBoost and Extra Tree ensemble classifiers performed better. Moradi et al. [8] tried to overcome the challenge of missing values in a dataset and presented an ensemble-based classifier for the Top-k recommendation problem. An ensemble regressor was put out by Schclar et al. [9] to forecast missing ratings in recommender systems. Karthikeyan et al. [10] proposed a system that uses XGBoost as an ensemble classifier to predict the risk of heart attacks with an accuracy of 90.1%. Xu et al. [11] have used XGBoost for commodity recommendation to predict whether the targeted user will buy a particular item or not. The proposed method however suffers from the cold start problem. Sales forecasting for retailers was carried out by Saradhi et al. [12] using XGBoost,

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Random Forest, and Linear Regression. When the proposed model's performance is assessed using customer, store, and geography data, it is found that XGBoost performs better than the other regressor models.

3 METHODOLOGY

The proposed research work undergoes the process of preprocessing in order to remove missing values and ensure data quality. The MovieLens dataset is first obtained, and a crucial step is to handle any missing values. This guarantees that the dataset is clean and ready for more analysis. Another critical phase in creating the movie recommender system is feature selection. We use feature selection approaches in our work to improve the effectiveness of the movie recommender system. The process of reviewing and selecting the most relevant features from the MovieLens dataset, such as movie genres, user demographics, and ratings, is known as feature selection. We try to enhance the precision and effectiveness of the recommender system by carefully selecting the relevant features. Fig 5. represents the framework of our proposed methodology. The subsequent steps in designing the movie recommender system are explained in detail below:

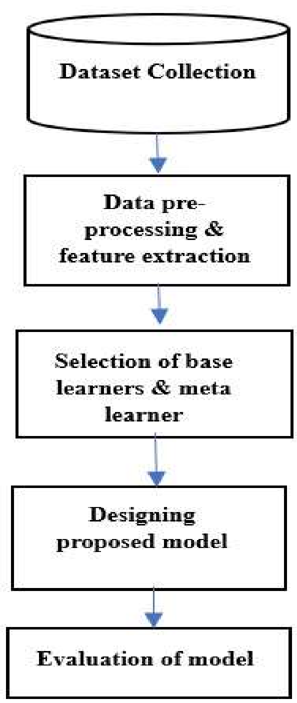

Figure 5: Framework for our proposed model

3.1 Dataset used

We used a 100K-byte dataset from the MovieLens website [14]. The collection includes files with information on movies, users, ratings and demographics. The fields user id, age, sex, zip code, and occupation are all included in the user file. The fields user id, movie id, rating, and timestamp are included in the rating file. The fields movie id, title, release date, video release date, and imdburl are all included in the movie file. We merged the dataset's movie, ratings, and user files to create a single file. The user's demographic data is not taken into consideration in this case.

3.2 Data Preprocessing

Data preprocessing is essential in Machine Learning because it includes altering, encoding, or transforming data into a format that machine learning models can successfully use. Several exploratory data analysis approaches are applied across all datasets during the data preprocessing step. The first step is to deal with any missing or null values in the data. Incomplete information or data input errors can result in missing values. One technique for dealing with missing data is to replace them with the average values of the respective attribute column. Predictive algorithms, on the other hand, can be used to estimate and fill in missing variables. The missing values were filled in this study by assigning the average values of the filled attribute column.

3.3 Feature Selection

During the feature selection process, we extract the relevant features from the dataset that are required for developing the recommender system. User ID, movie ID, rating, timestamp, title, release date and video release dateare all included in the dataset we used for our analysis. However, in this scenario, we do not take into account the user's demographic information.

Categorical features are translated into numerical representations using techniques such as one-hot encoding to aid effective modeling. This translation allows the models to easily interpret and handle category features. We identified and considered the following features for our suggested models after performing feature selection: user ID, movie ID, year, and rating. The snapshot of our

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proposed model showing the features selected is shown in Fig 6.

	movieId	year	userId	rating
0	1	1995	1	4.0
1	1	1995	5	4.0
2	1	1995	7	4.5
3	1	1995	15	2.5
4	1	1995	17	4.5

Figure 6: A snapshot of features selected for our proposed model

3.4 Selection of base learner and meta learner

To determine the ideal base learner and meta-learner combination for our proposed recommender system, we tested a variety of base learner and meta-learner combinations. We have experimented with four ensemble models for base learners: Gradient Boost (GB), AdaBoost (AB), Random Forest (RF), and XGBoost or eXtreme Gradient Boosting. We have used two regression models for base learners: Linear Regressor (LR) and K-Nearest Neighbors Regressor (KNN) (XGB). We have tested with the XGBoost and Linear Regressor models as meta-learners. Description of the models used are given below:

3.6.1 Linear Regressor

The linear regression model is a statistical technique for modeling the relationship between one or more independent variables and a dependent variable.

The model is written as a linear equation:

Y = an*Xn + a0 + a1X1 + a2X2 +...anXn

Y is the dependent variable, X1, X2,..., Xn are the independent variables, a0 is the intercept, and a1, a2,...,an are the coefficients that determine how each independent variable affects the dependent variable.

3.6.2 XGBoost

An extreme gradient boosting (XGBoost) regressor is an advanced machine learning technique that uses gradient boosting to build highly accurate regression models. It includes several changes to boost efficiency and properly handle complicated datasets. XGBoost is a popular alternative for regression tasks since it is an optimized implementation of the gradient boost technique of machine learning.

3.6.3 Random Forest Regressor

A random forest regressor is a machine-learning model made up of a group of decision trees. Each decision tree is built with a randomly chosen subset of the training data and features. The model generates the final result by combining predictions from numerous decision trees, improving accuracy, and handling complex data interactions.

3.6.4 Gradient boosting

Gradient boosting is a powerful machine learning technique that builds a strong predictive model by iteratively mixing weak prediction models, commonly decision trees.

3.6.5 AdaBoost

Adaptive boosting, often known as AdaBoost, is an ensemble learning method that begins by giving each training instance identical weights. It then trains a weak model on the data and modifies the weights based on the previous model's faults.

3.6.6 K-nearest neighbors (KNN)

K-nearest neighbors (KNN) is a basic yet powerful machine learning technique that can be used for both classification and regression tasks. It operates on the premise of locating the K closest data points in the feature space to a particular query point and producing predictions based on the majority vote or average of those neighbor's labels or values.

3.5 Proposed Model

In Fig. 7, the diagrammatic form of our proposed ensemble recommender system is presented. Stacking involves two or more different base models or learners in the first layer and then the output of the first layer is used to train the meta-learner which is yet another learner in the second

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layer as shown in Fig. 7. To create the final prediction, the meta-learner in the first layer integrates the predictions generated by the base learners..

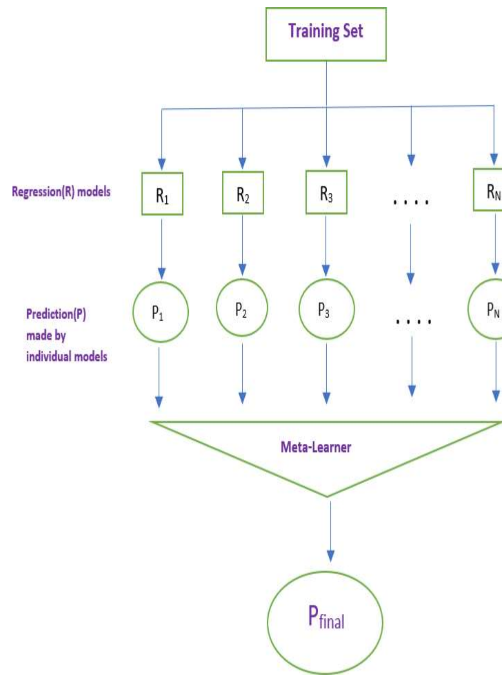

Figure7: A diagrammatic representation of the proposed stacking-based ensemble learner

In stacking, the meta-learner is considered to be stacked on top of the base learners and therefore the name is stacked model or stacking.

3.6 Evaluation of model

Metrics used to evaluate our proposed model are are Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Mean Squared Error (MSE).

3.6.1 The mean absolute error (MAE)

The mean absolute error (MAE) is calculated by adding the absolute differences between the actual and estimated values for each observation and then dividing the total by the number of observations. MAE evaluates the average magnitude of mistakes made by an estimator or prediction model.

Formula for MAE, $\frac{1}{n}\sum_{i=1}^{n}|y_i - y_i'|$

Here,

n is the number of observations

$y_i$represents the observation's actual values

3.6.2 Root Mean Squared Error (RMSE):

The RMSE is a measure of the average squared difference between the estimated and actual values.

Formula for RMSE, $\sqrt{\sum_{i=1}^{n}\frac{(y_i'-y_i)^2}{n}}$

Here,

n is the number of observations

$y_i$represents the observation's actual values

y_i' represents the estimated or predicted values

3.6.3 Mean Squared Error (MSE

Mean Squared Error (MSE) is a popular statistic for assessing the performance of regression models. The average of the squared differences between the expected and actual value is calculated.

4 RESULT

Python 3.8.5 has been used to implement the proposed movie recommendation system. The MovieLens dataset, which is discussed in section 3, was used.Table 1 presents the experimental findings for each learner when they were used independently. A comparison of the RMSE values obtained for base learners when used independently is shown in Fig. 8.

Table 1: RMSE of different learners used in a stand-alone manner

Model	RMSE
Linear Regressor (LR)	1.08
XGBoost (XGB)	**0.92**
Random Forest (RF)	0.98
AdaBoost (AB)	0.96
Gradient Boost (GB)	0.99
K-Nearest Neighbors (KNN)	1.07

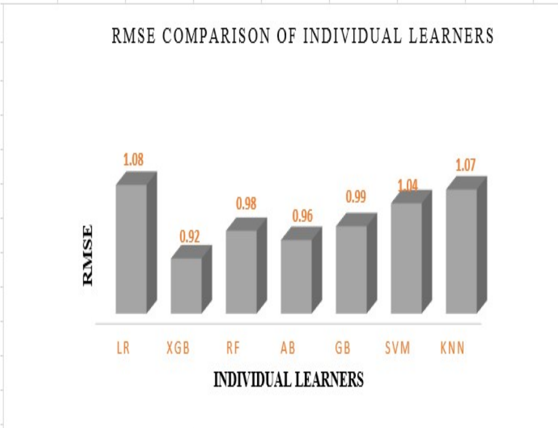

Figure8. RMSE comparison of different learners used in a stand-alone manner

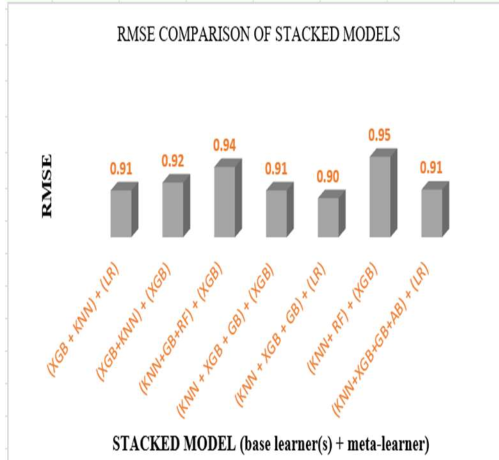

Fig. 9. Comparative view of the accuracy values obtained for these stacked models

Next, we tested various combinations of base learners and meta-learners, or different stacked models. In Table 2, the outcomes from various stacked models are displayed. However, we have limited Table 2 to those stacked models that have comparatively improved accuracies. Fig. 9. presents a comparative view of the accuracy values obtained for these stacked models.

Table 2: Accuracy of different Stacked models

Base Models	**Meta-Learner**	**RMSE**
XGB + KNN	LR	0.91
XGB + KNN	XGB	0.92
KNN + GB + RF	XGB	0.94
KNN + XGB + GB	XGB	0.91
KNN + XGB +GB	LR	**0.90**
KNN + RF	XGB	0.95
KNN + XGB + GB + AB	LR	0.91

We have also calculated the Mean Squared Error (MSE) and Mean Absolute Error (MAE) values for the stacked model for which we have got comparatively lowerRMSE values and presented in Table 3. Our proposed model achieved an MAE of 0.69, MSE of 0.81, and RMSE of 0.90, indicating its superior performance compared to the existing model.

Table 2: MSE, MAE, and RMSE of the proposed stacked model

Base Models	KNN+ XGB + GB
Meta-learner	LR
MSE	0.82
MAE	0.69
RMSE	0.90

5 CONCLUSION

A stacking-based ensemble movie recommender system has been put out in this paper. Our primary goal in this research is to create a movie recommendation system that not only provides accurate predictions but also represents the diversity and complexity of consumers' movie choices. Traditional recommendation techniques frequently struggle to strike a balance between accuracy and diversity. We hope to achieve a balance between these features through our investigation of the stacking technique, resulting in

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a recommendation system that not only matches user expectations but also pleasantly surprises them with suggestions they might not have considered otherwise.To create an effective stacked model, many base-learner and meta-learner combinations have been investigated. The experimental results that we obtain have led to many interesting observations:

- An ensemble system based on stacking typically performs better than standalone systems.
- In the stacked model proposed for our ensemble movie recommender system, XGBoost and Linear Regressor are suitable options for meta-learners
- XGBoost performs exceptionally well both as a base learner and as a meta-learner in the proposed stacked model. In our proposed model, XGBoost is found to perform better than other stand-alone models even when used alone.

While the study presents a promising approach to movie recommendation using a stacking-based ensemble, a more thorough analysis of model selection, dataset characteristics, performance metrics, and critical evaluation would enhance the overall credibility and impact of the research. Addressing these points would not only strengthen the findings but also provide a solid foundation for future advancements in the field of recommendation systems.Future research might extend on this work by investigating the performance of alternative advanced algorithms within the stacking-based ensemble framework, creating dynamic recommendation systems that adapt to changing user preferences and incorporating user-specific features for personalization. It may also involve creating a multi-layered stacking model to improve the proposed stacked model's accuracy. Several combinations of base learner(s) and meta-learner(s) might be tested to find a more effective stacked model. To reach a more thorough understanding of the proposed system's adaptability, it can also be examined across a variety of application domains.

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