Content Suggesting System based on the user's personality and current mood

Project No.87

M.K. Damindu Pahasara (AA1680), A.S. Bandarathilaka (AA1706)

Supervised by Mr. Dinith Primal (Supervisor)

School of Computing and IT

Sri Lanka Technology Campus, Ingiriya Road, Meepe, Sri Lanka

avishkabs@sltc.ac.lk | damindup@sltc.ac.lk

Abstract

The development of digital media on the internet has changed the way we consume entertainment, yet consumers still have trouble finding material that speaks to their interests and personalities. Traditional recommendation systems that prioritize popularity or genre are ineffective. This study presents an innovative approach for making more accurate recommendations: personality profiling and current mood assessment. Impressive accuracy rates were achieved by an advanced neural network model: 98.82% during training and 99.31% during testing. With intentions to expand to other media, the algorithm only recommends movies and TV shows at the moment. About fifty users' responses confirmed its efficacy and provided suggestions for improvements in the future.

Introduction

- Books, TV series, movies, music, articles, and photos are all types of online media.
- Because of digital platforms, media may be accessed and shared globally via the internet.
- Through social media, online retailers, and streaming services, users have easy access to a variety of material.
- It can be difficult to locate customized material even with its quantity.
- Present-day recommendation systems are generally imprecise, concentrating on narrow parameters such as media genres or emotional states.
- Are content recommendations improved based on personality and mood?
- To provide personalized recommendations, the suggested approach examines the user's personality and emotional state.

Objectives

- Identify the personality of users.
- Detect the current mood of the user.
- Identify the related content for both personality and mood.
- Recommend digital content for users.
- Store users (Personality) and content data.

Research Method

System Diagram

Personality Detection Process

- Use a personality questionnaire to identify user personality.
- Utilize AWS Rekognition for mood detection.
- Combine mood and personality data as model input.
- Generate personalized content recommendations via the model.
- Retrieve recommended movies and TV shows from TMDB via API call.
- Display recommended content to the user for seamless access.

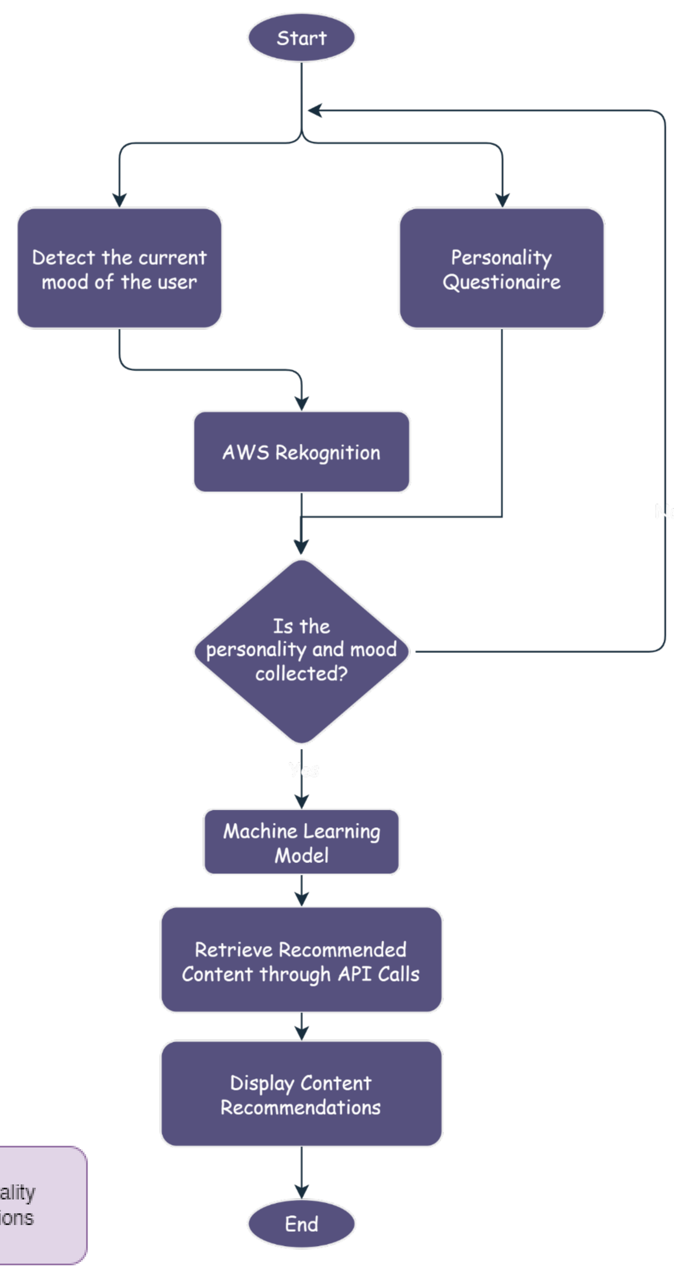

Figure1: System Diagram

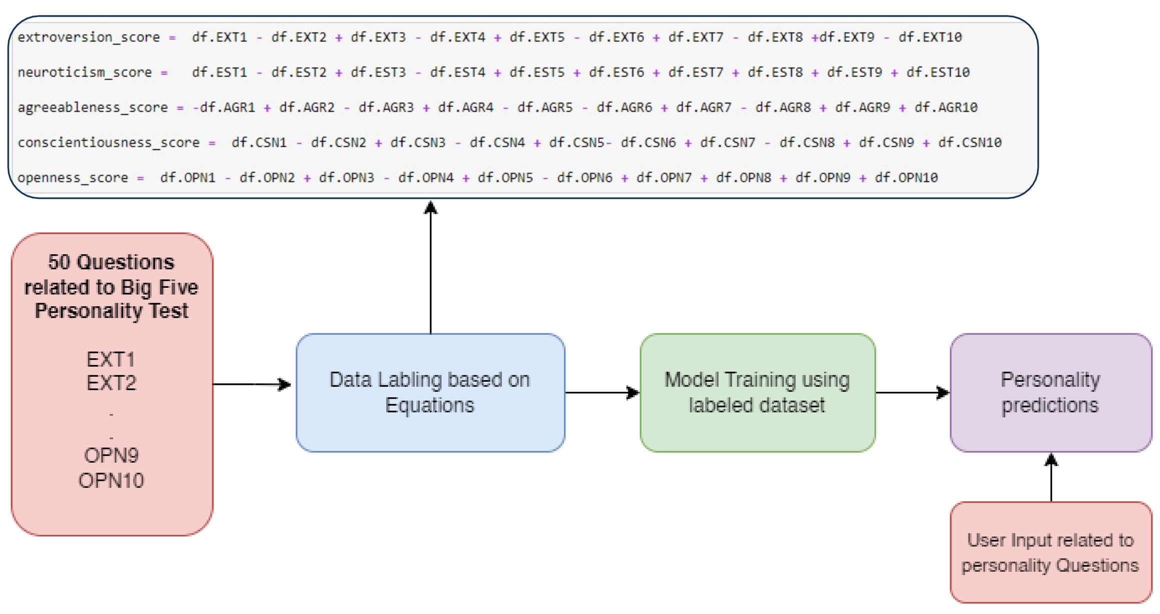

Figure2: Personality Detection

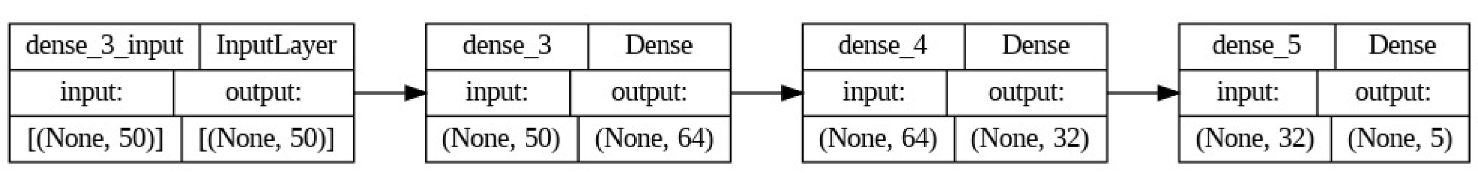

Figure3: Visualization of Artificial Neural Network

- Collect user input data for 50 personality questions based on the Big Five personality traits.
- Apply predefined equations to label user data according to personality traits.
- Feed labeled user inputs into the trained artificial neural network (ANN) model.
- Obtain personality predictions from the model based on the input data..

Recommendation process

- Implemented the recommendation process using two distinct methods.
- The first method relies on natural language processing.
- Initially, it recommends a single content based on users' personality and current mood.(Figure4)
- Subsequently, it utilizes the NLP model to recommend additional content.
- Due to the main use of the NLP model in the recommending process, we developed our own algorithm as the second method.
- This algorithm is based on the findings from the research titled [1] "We Are What We Watch: Film Preferences and Personality Correlates".(Figure5)

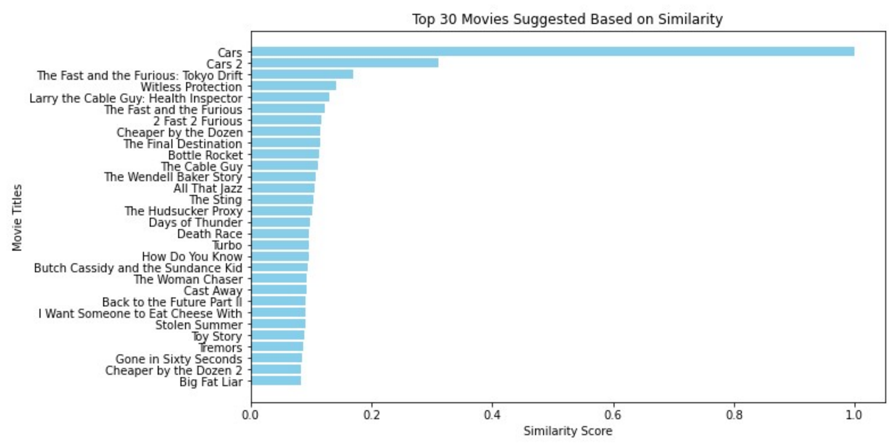

Figure4: Similarity score based on "cars" input in NLP

Correlations

		Action	Comedy	Documentary	Drama	Horror	Romance	Sci Fi
Extra.	Pearson Correlation	.000	.199**	.063	.113	-.027	.266**	-.139
	Sig. (2-tailed)	.996	.008	.406	.132	.720	.000	.063
	N	179	179	179	179	179	179	179
Agree.	Pearson Correlation	-.014	.137	.073	.087	-.064	.278**	-.085
	Sig. (2-tailed)	.856	.067	.330	.245	.396	.000	.258
	N	179	179	179	179	179	179	179
Consc.	Pearson Correlation	.021	.014	-.027	.120	.040	.198**	-.081
	Sig. (2-tailed)	.779	.847	.725	.111	.597	.008	.284
	N	179	179	179	179	179	179	179
Neurot.	Pearson Correlation	.130	-.047	.100	-.075	-.095	-.109	-.179*
	Sig. (2-tailed)	.083	.535	.182	.318	.206	.146	.017
	N	179	179	179	179	179	179	179
Open.	Pearson Correlation	-.030	-.076	.269**	.163*	.128	.111	.216**
	Sig. (2-tailed)	.693	.314	.000	.030	.088	.139	.004
	N	179	179	179	179	179	179	179

Figure5: Score matrix from "We are What We Watch" Research

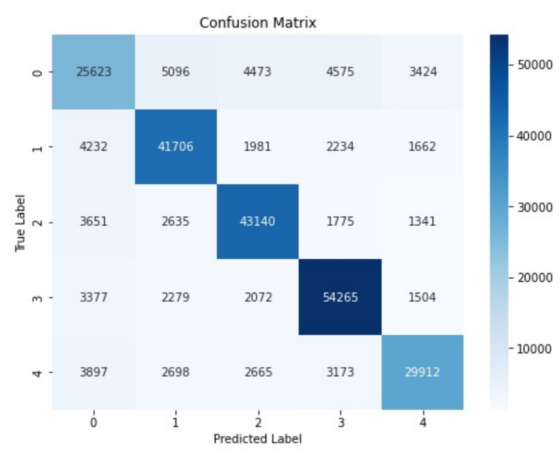

Figure6: Random forest confusion matrix

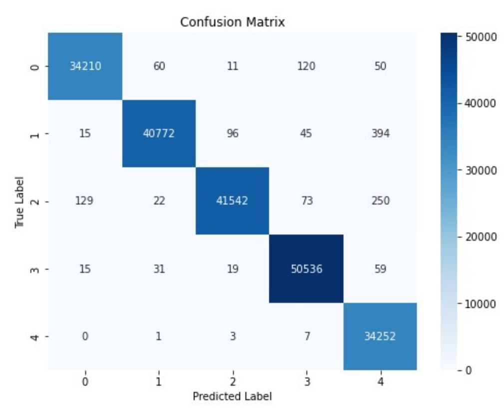

Figure7: Artificial Neural Network confusion matrix

Results & Discussion

- After training the dataset using ensemble methods, it was observed that among them, the random forest algorithm yielded the highest performance. The accuracy score achieved by the random forest model was **76.81%**, as depicted in the accompanying figure6.
- Subsequently, the dataset underwent training using an artificial neural network (ANN). Remarkably, the ANN achieved a testing accuracy score of **99.31%**, as illustrated in the provided figure7.
- Notably, the dataset utilized for training the artificial neural network was a balanced dataset, ensuring equitable representation across all classes, as indicated in the figure8.

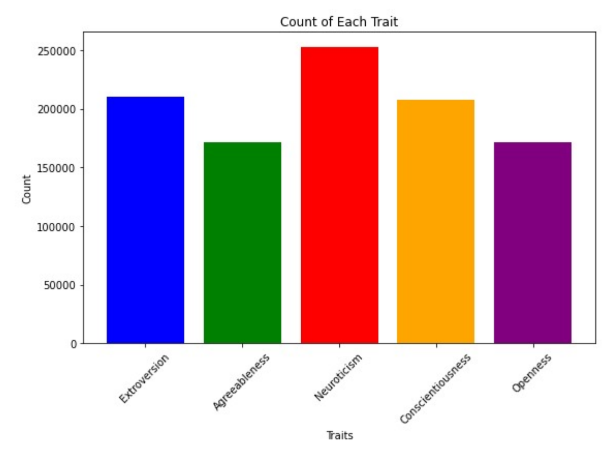

Figure8: Personality Distribution in Training Dataset

- After integrating the machine learning model, mood recognition function, and personality questionnaire within the Flask web framework, alongside HTML and JavaScript components, the resulting web application was deployed on an EC2 instance hosted on AWS.

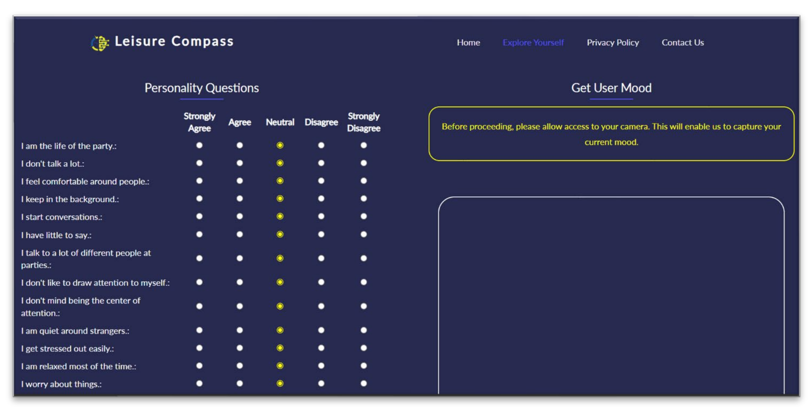

Figure9: Personality questionnaire and mood detection

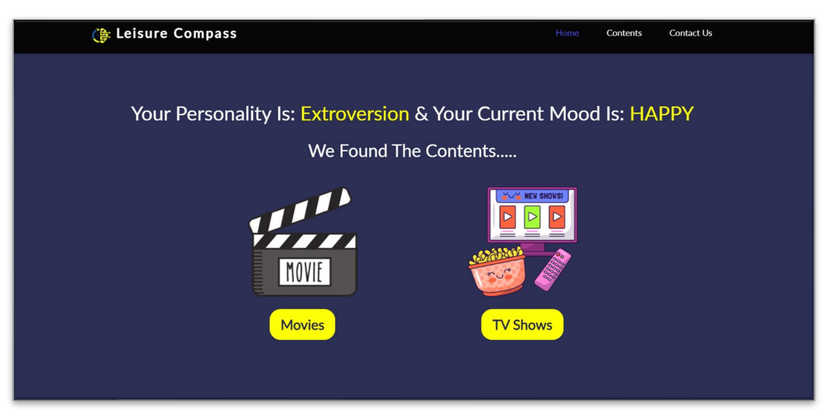

Figure10: Recommended content – Movies & TV Shows

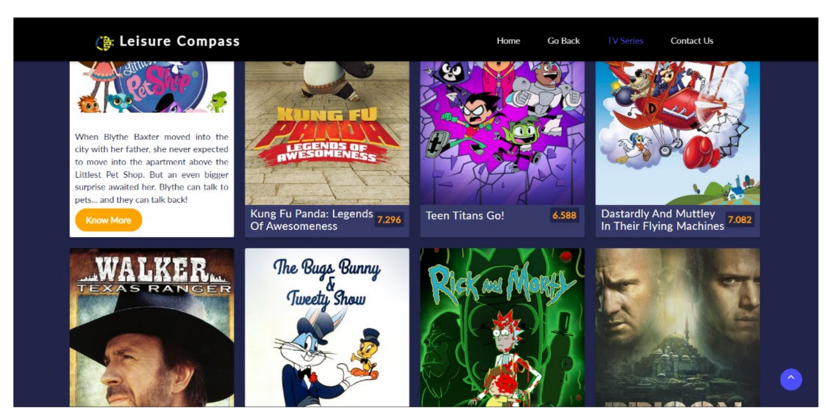

Figure11: TV Shows

Conclusion

- Our study introduces a novel method for personalized content recommendation, leveraging user mood and personality profiling.
- Through advanced analysis, our system delivers accurate content suggestions.
- The integration of an artificial neural network underscores the effectiveness of our recommendation framework.
- While initially focused on movies and TV shows, future iterations will expand to diverse media content.
- User feedback refines system performance.
- Deployment on AWS ensures seamless access and scalability.
- In summary, our innovative system enhances entertainment experiences with precision.

References

[1] A. Romans, We Are What We Watch: Film Preferences and Personality Correlates, 2015
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[3] content recommendation system based on facial expression recognition," in 2012 IEEE International Symposium on Multimedia, pp. 84–87, IEEE, 2012.
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