SOCIAL-NETWORK REPRESENTATION LEARNING RECOMMENDATION ALGORITHM

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ABSTRACT

Network representation learning has proven its usefulness in many activities such as photography or text mining. A goal of network representation learner is to learn distributed vector representation for each vertex in the network. An essential feature of network analysis is now increasingly recognized. A social-network-based recommendation algorithms is limited by the coarse-grained and sparse trust relationships. we first adopt a network representation technique to embed social network into a low-dimensional space, and then utilize the low-dimensional representations of users to infer fine-grained and dense trust relationships between users.With the popularity of social network applications, more and more recommender systems utilize trust relationships to improve the performance of traditional recommendation algorithms. Social-network-based recommendation algorithms generally assume that users with trust relations usually share common interests. However, the performance of most of the existing social-network-based recommendation algorithms is limited by the coarse-grained and sparse trust relationships. In this paper, we propose a network representation learning enhanced recommendation algorithm. Specifically, we first adopt a network representation technique to embed social network into a low-dimensional space, and then utilize the low-dimensional representations of users to infer fine-grained and dense trust relationships between users. Finally, we integrate the fine-grained and dense trust relationships into the matrix factorization model to learn user and item latent feature vectors. The experimental results on real-world datasets show that our proposed approach outperforms traditional social-network-based recommendation algorithms.

1 INTRODUCTION

In the era of big data, it becomes increasingly difficult and valuable related information from massive unstructured data. Therefore, recommender systems have become an effective means to solve the problem of information overload. In recent years, Typical applications of recommender systems include Amazon's product recommendation, LinkedIn's friend recommendation, and Google News's news recommendation. Social networks naturally form graph structures where nodes represent users and edges represent the relationships or interactions between them. In recent years, social networks have become an integral part of our daily lives, serving as platforms for communication, information dissemination, and entertainment. The sheer volume of data generated by user interactions, friendships, and shared content provides a rich resource for developing sophisticated recommendation systems. These systems aim to enhance user experience by suggesting relevant content, potential connections, and personalized advertisements. One of the cutting-edge approaches in this domain is social network representation learning. This method leverages the structural information of social networks to learn low-dimensional representations (embeddings) of nodes (users, posts, etc.). These embeddings capture the intrinsic properties and relationships within the network, enabling more accurate and efficient recommendations.

Literature Survey

A literature survey for social network representation learning and recommendation algorithms involves reviewing key research papers, methodologies, and findings in these areas. Below is a structured overview of important themes and influential works in this field.

- **Node Embeddings**: Low-dimensional vectors representing nodes in a network.
- **Graph Neural Networks (GNNs)**: Deep learning methods designed to work directly with graph-structured data.
- **Matrix Factorization**: A traditional method for recommendation that can be adapted to incorporate social network information.

3 IMPLEMENTATION STUDY

EXISTING SYSTEM:

The existing systems for social network representation learning and recommendation algorithms are evolving rapidly with advancements in deep learning and scalable algorithms, aiming to better understand and utilize the social structures and interactions within networks.

Disadvantages:

- In the existing work, typical social-networks only integrate observed explicit trust relationships, and ignore the implicit trust relationships.
- The system is less effective due to lack of recommendation algorithm.

Proposed System & alogirtham

In our proposed system, we generally apply the LINE model to learn user's embedded representations of the social network. It is aim to learn low-dimensional vector representations for nodes in a network such as social networks, citation networks, or biological networks while preserving their structural and relational learning properties.

4.1 Advantages:

- Network representation learning techniques embed the large-scale information network into the low-dimensional space, and each network node is represented as a low dimensional vector.
- Deep Walk which is effectively implemented adopts a random walk algorithm to learn the embedded representations.

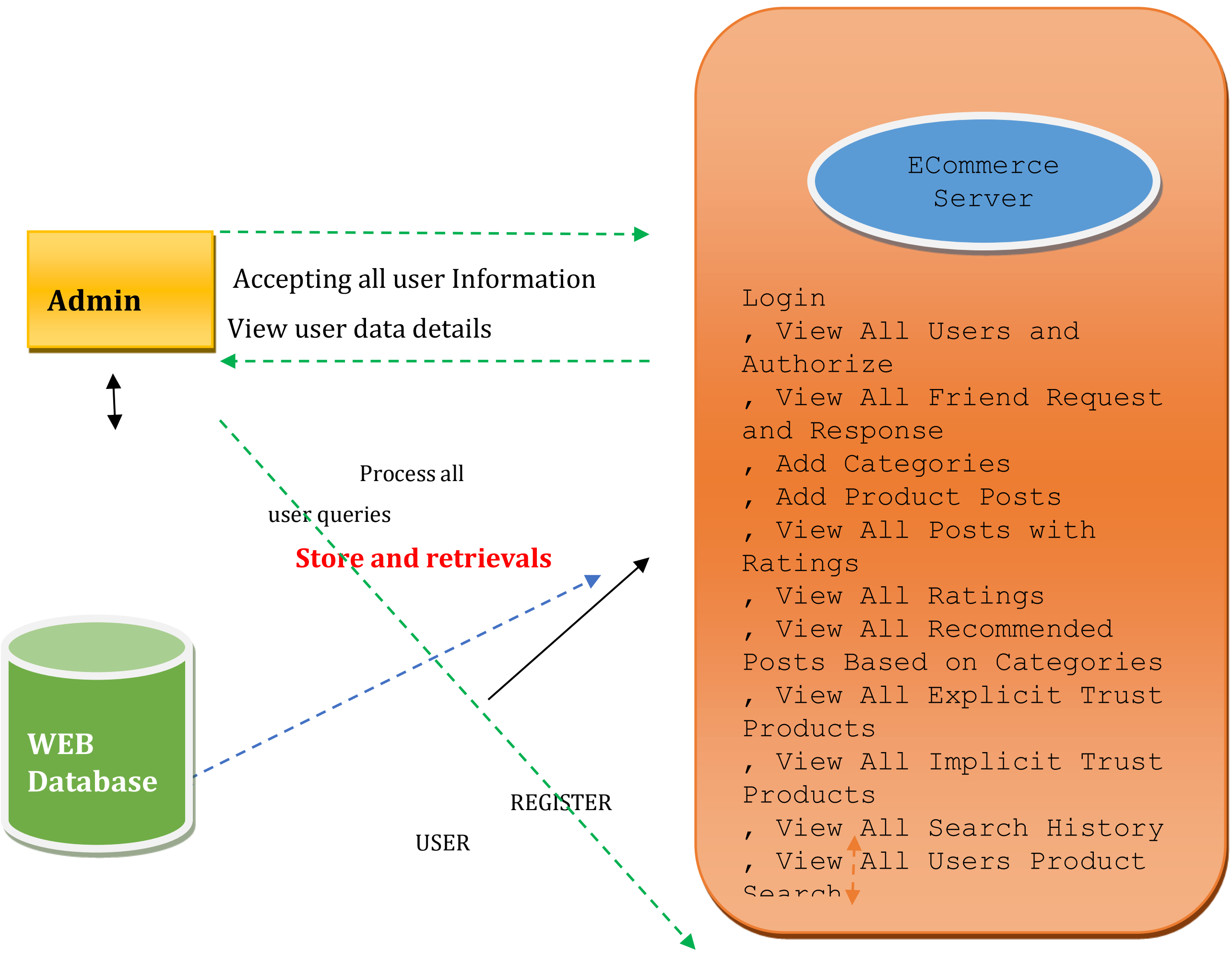

Fig:3.1 System Architecture

IMPLEMENTATION

4.1 MODULES

- **ECommerce Server:**

In this module, the server has to login by using valid user name and password. After login successful he can perform some operations, such as View All Users and Authorize, View All Friend Request and Response, Add Categories, Add Product Posts, View All Posts with Ratings, View All Ratings, View All Recommended Posts Based on Categories, View All Explicit Trust Products, View All Implicit Trust Products.

Viewing and Authorizing Users

In this module, the Server views all users' details and authorize them for login permission. User Details such as User Name, Address, Email Id and Mobile Number.

Adding Categories and Posts

In this module, the admin adds Categories and Posts with Details such as Category Name, Post Name, Description and Post Image.

- **User**

In this module, there are n numbers of users are present. User should register before performing any operations. Once user registers, their details will be stored to the database. After registration successful, he has to login by using authorized user name and password. Once Login is successful user can perform some operations like Search Friends and Request, View Friend Requests, Search Posts, Recommend to Friend, My Search History, View All Product Recommends.

5 RESULTS AND DISCUSSION

SCREENSHOTS

LOGIN PAGE

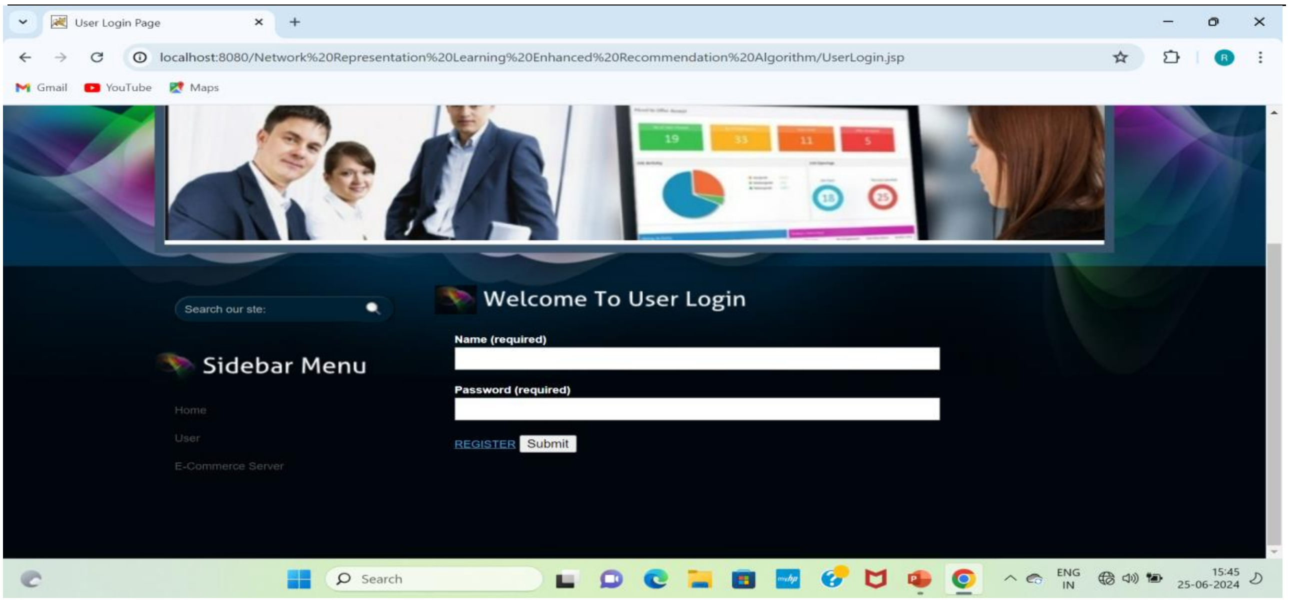

Fig: Login

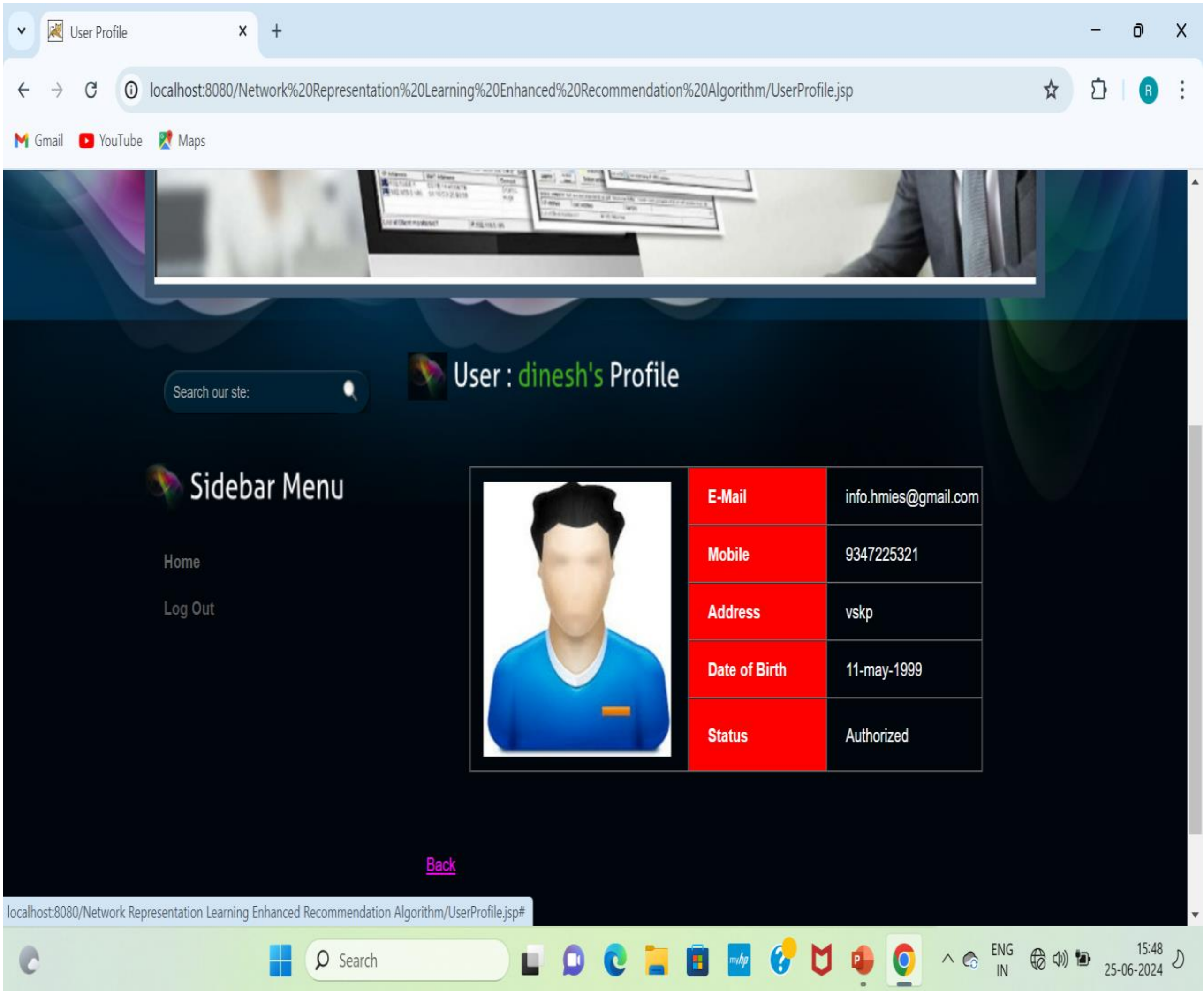

Fig : View Profile

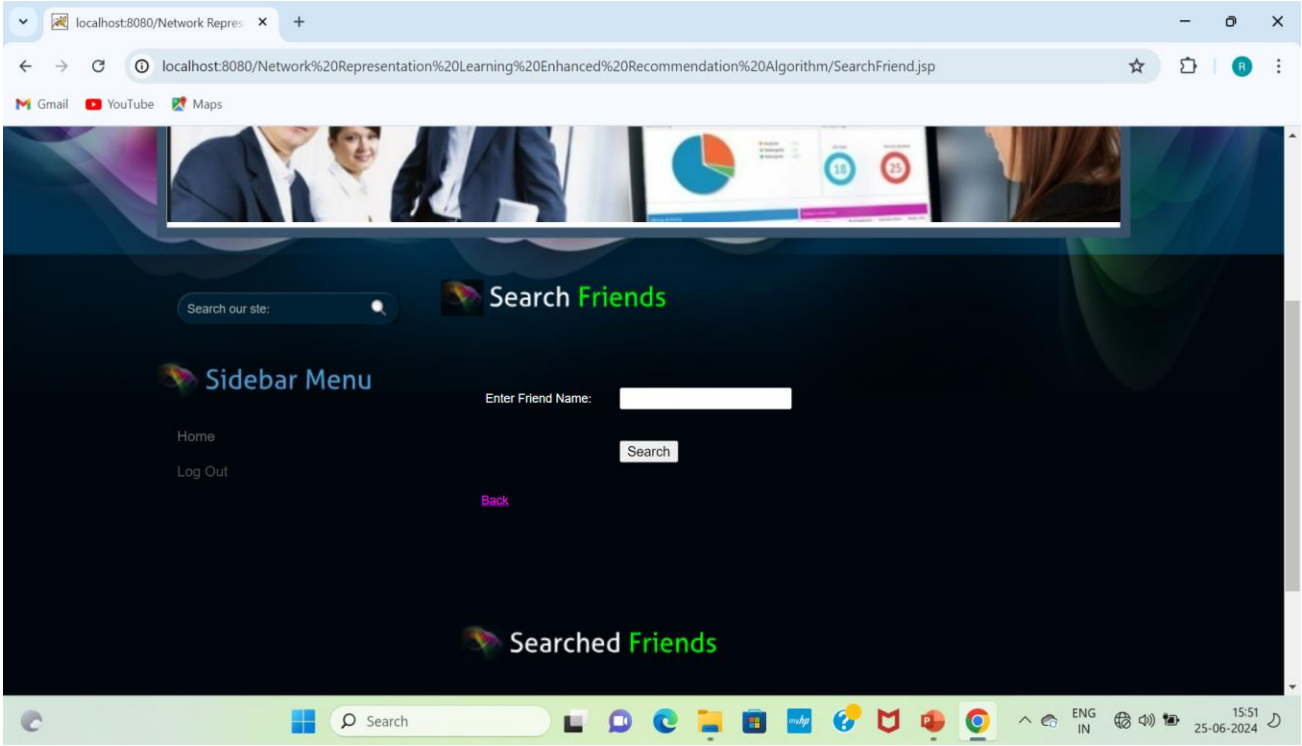

Fig : Search Friends

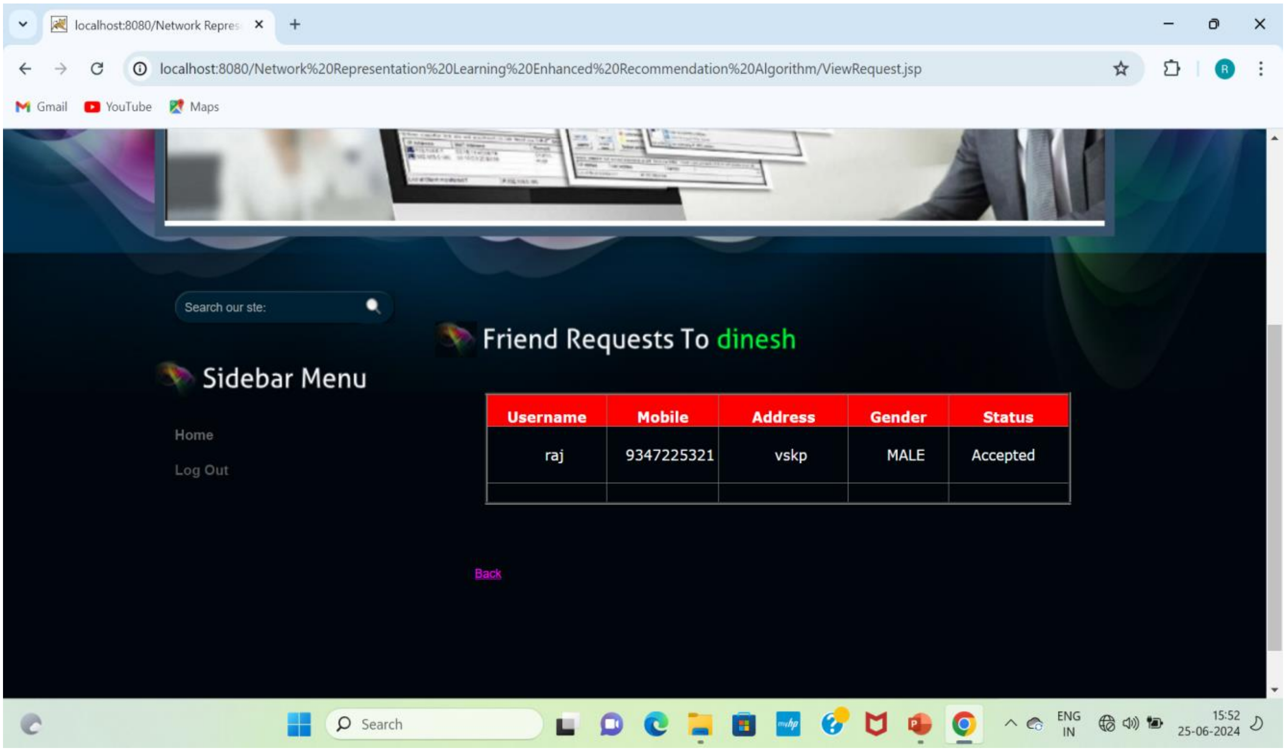

Fig : View Friend Request

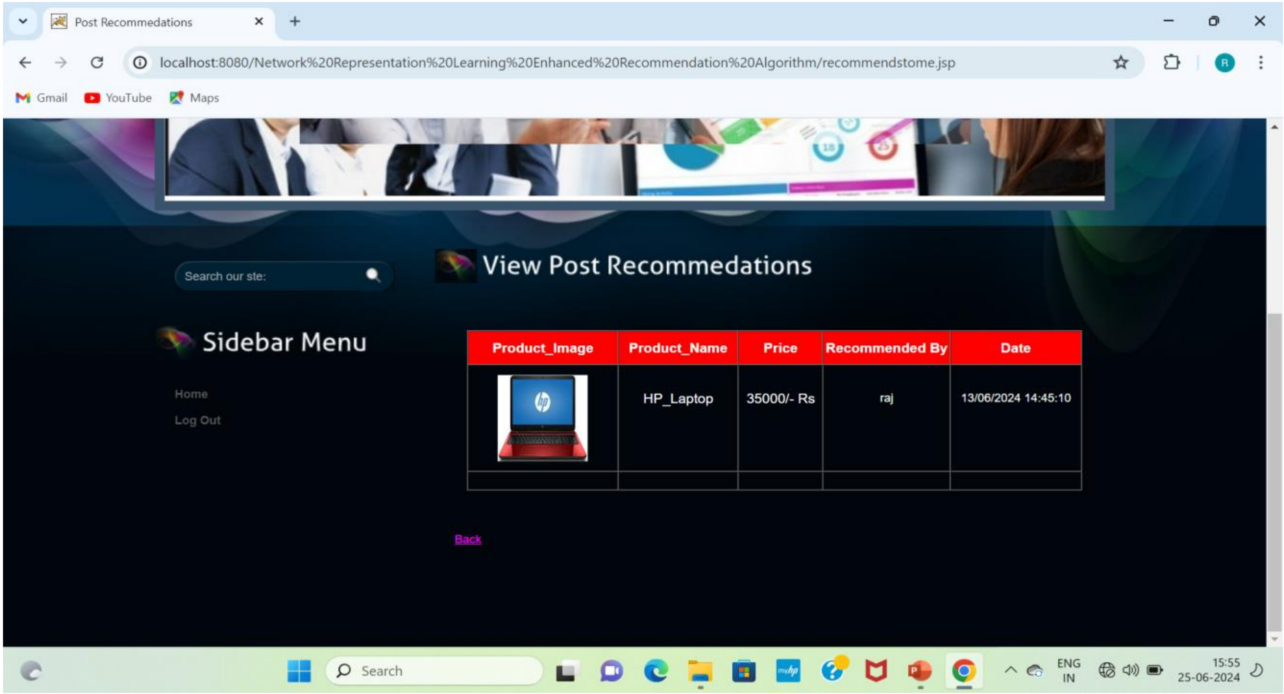

Fig : View Post Recommendation

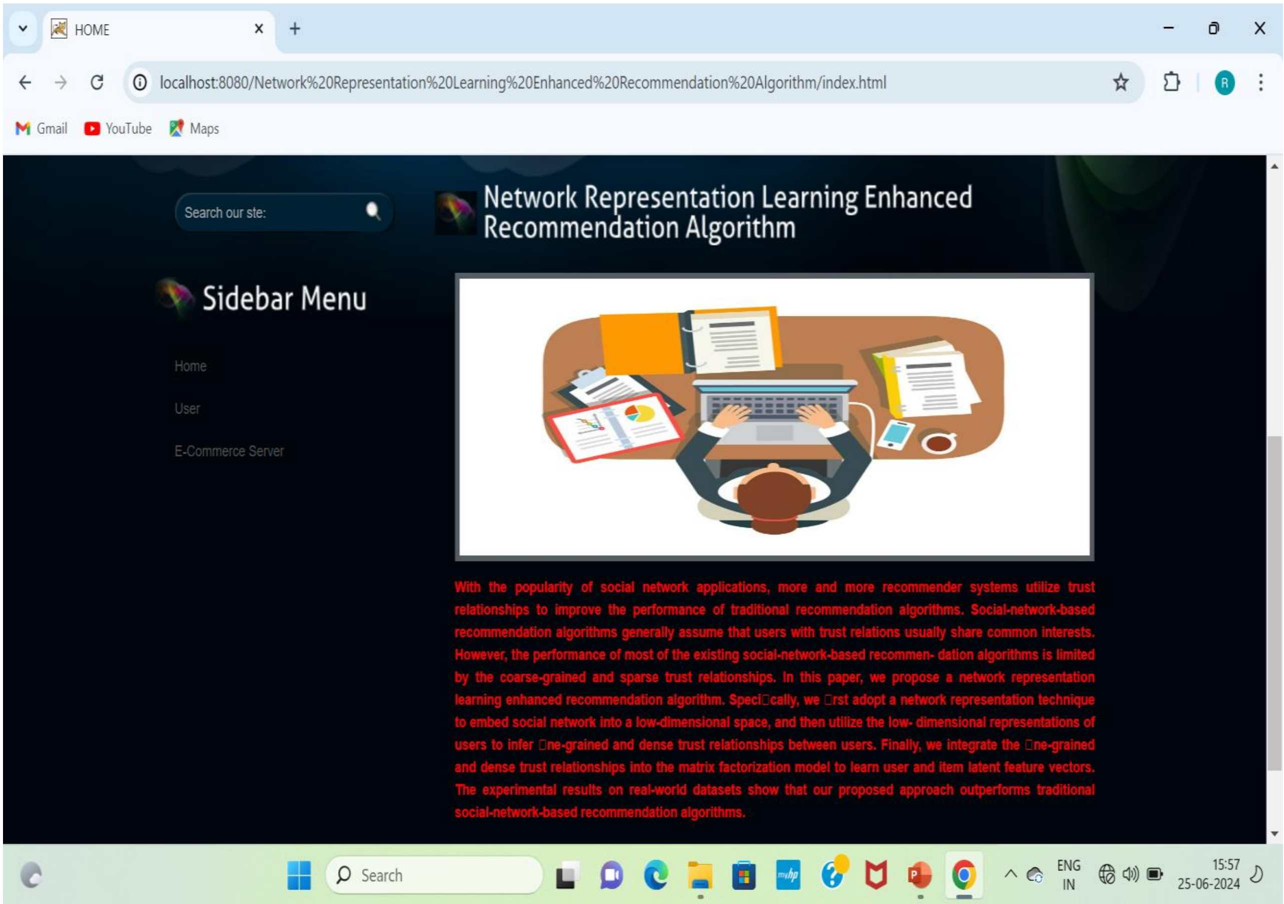

Fig : Logout

6. CONCLUSION AND FUTURE WORK

CONCLUSION

Social media has really made the world a smaller place, we can now do business with people from all over the world so much easier and quicker than ever before. Social media is here to stay and you start learning how to use it to its full potential. The impact of social media on society is undeniable. It has revolutionized the way we communicate, share the information, had connect with others. Traditional social-network-based recommendation algorithms generally utilize the coarse-grained trust relationships to generate recommendations, which seriously hinders the performance of recommendation algorithms. To tackle this problem, we proposed a network representation learning enhanced recommendation algorithm in this study. Specially, we first adopt a network representation learning technique to embed a social network into a low-dimensional space, and then utilize the low-dimensional representations of users to infer ne-grained dense trust relationships between them.

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