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User Behavior Prediction of Social Hotspots Using Interaction with Multiple Messages and Neural Networks

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***Abstract:** The variety of communications under social hot topics has a significant impact on user engagement behaviour in network public opinion study. This article suggests a prediction model of user participation behaviour during repeated messaging of trending social issues, taking into account interactions between numerous messages and complicated user behaviours. A multimessage interaction influence-driving method was first presented to better precisely forecast user involvement behaviour by taking into account the impact of multimessage interaction on user participation behaviour. Second, this study proposes a user participant behaviour prediction model of social hotspots based on a multimessage interaction-driving mechanism and the BP neural network. This is done in light of the behavioural complexity of users participating in multimessage hotspots and the simple structure of backpropagation (BP) neural networks (which can map complex nonlinear relationships).*
***Keywords:** Multimessage interaction, social hotspots, user behaviour, and backpropagation (BP) neural network*

I. INTRODUCTION

The ways in which people communicate and live have changed dramatically. The creation and sharing of trending topics on social media has an ongoing impact on how individuals conduct their daily lives. The user's reading and responding to messages in the network, as well as the social network's structure, encourage the spread of network themes and the transmission of information about hot subjects. Understanding user-forwarding participation behaviour is crucial for information retrieval, network monitoring of public opinion, and assessing the impact of a microblog issue. Presently, the following two methods are primarily used to forecast user behaviour in social networks. The first method examines the structural topology map that social networks employ to distribute information and forecasts the flow and spread of the information.

II. EXISTING WORK

The user network topology and user fundamental information are taken into account in the majority of existing models when predicting user involvement behaviours, however the influence of messages spread under hot themes is ignored.

1) Sheikhahmadi et al. established a two-level approach that recognises and categorises user influence by taking into account user engagement.
2) Colombo and colleagues developed a topological map for examining how information spreads across social networks.
3) The majority of current studies use conventional machine learning techniques to anticipate the nonlinear relationships between the topic data input and the user participation behaviour output. By using several machine-learning techniques, Lee et al. predicted the user forwarding behaviour and the time of forwarding.

III. PROPOSED WORK

1) Based on several message interactions, a model for predicting user engagement behaviour is created. The multi message interaction-driving method increases the accuracy of the prediction findings by building on the mapping correlations between the fundamental user information and participation behaviour under the conventional single message. It is more accurate to discuss the process of communication diffusion in the interim.
2) A multi-message interaction-based quantization approach is suggested. By quantitatively assessing the mutual influence of messages from the standpoint of subjects, this article may more precisely evaluate the multiple message selection process within the user community. The same topic's hidden influence, which affects how users participate, can be qualitatively measured in the meanwhile.

3) The simulated annealing approach enhanced the performance of the BP neural network. The nonlinear relationship between the topic data input and the predicted user behaviour output is nicely matched by this strategy. Additionally, the simulated annealing approach resolves the neural network over fitting problem, substantially increasing prediction accuracy.

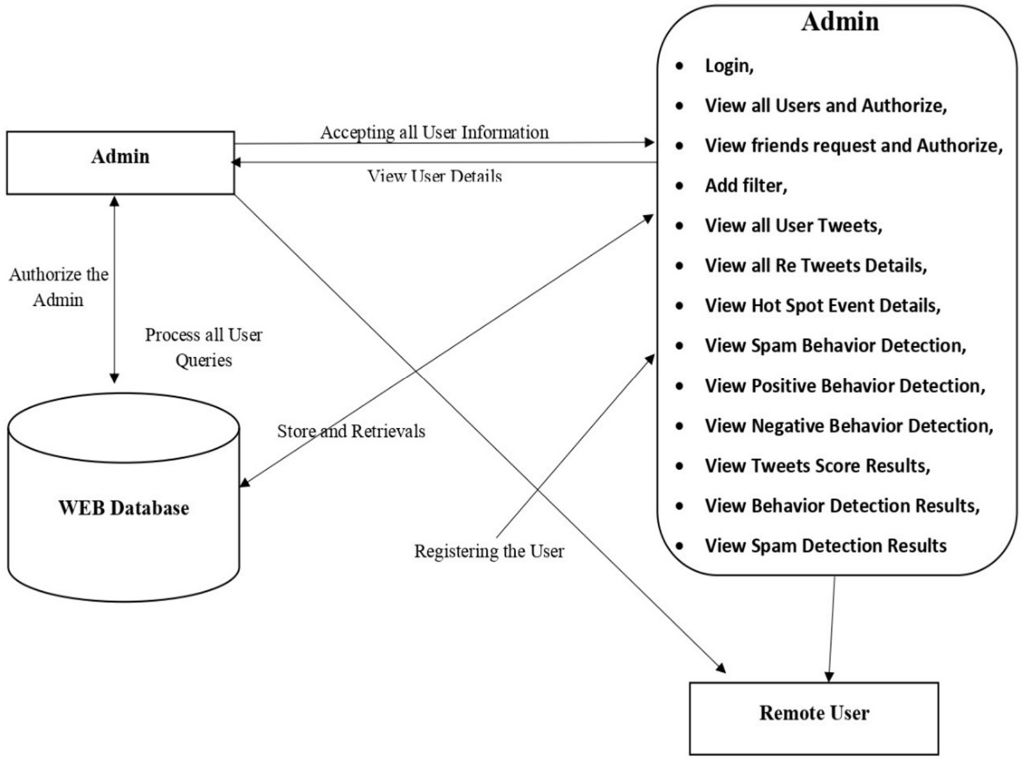


Fig. Model Diagram for Predicting User Behavior

IV. PREFATORY

A. *LSTM (Long Short-Term Memory)*

Recurrent neural networks include long short-term memory. The output from the previous phase is sent into the current step of an RNN as input. Hochreiter & Schmidhuber created LSTM. It addressed the issue of long-term RNN dependency, in which the RNN can predict words from current data but cannot predict words held in long-term memory. As the gap length grows, RNN's performance becomes ineffective. By default, LSTM may store information for a long time. It uses time series data for processing, forecasting, and classification.

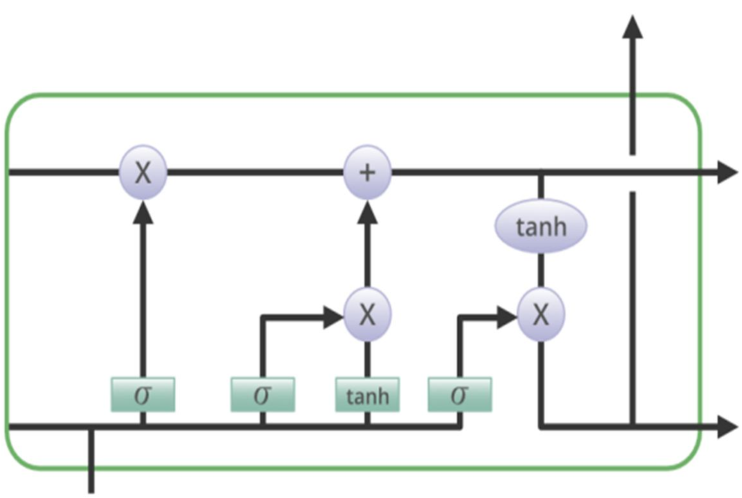


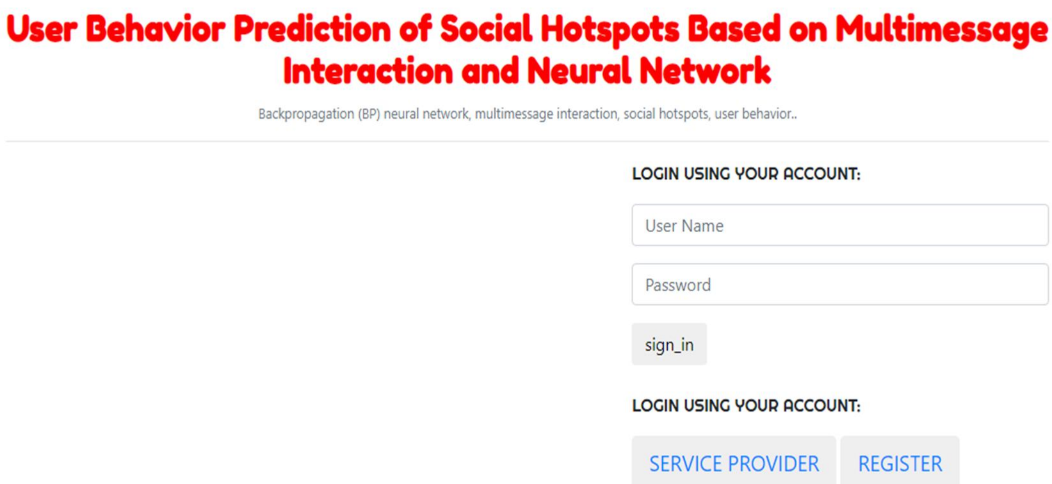
Figure: LSTM Organization

Cells and gates both play a role in memory modification and information retention. Three gates are present:

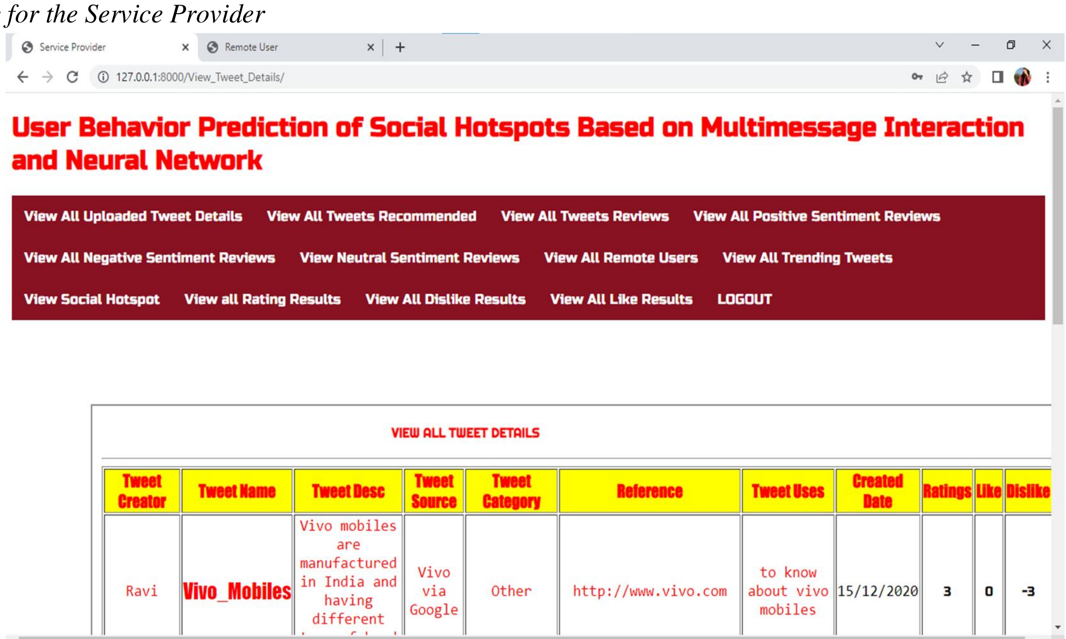
1) *Forget Gate:* The forget gate eliminates information that is no longer relevant to the condition of the cell. The gate receives two inputs, x t (input at the current time) and h t1 (prior cell output), which are multiplied with weight matrices before bias is added. The output of an activation 40 function that receives the resultant is binary. If the output for a certain cell state is 0, the information for that cell is lost, however if the output is 1, the information is saved for use in the future.
2) *Input Gate:* The input gate adds useful information to the cell state. First, The sigmoid function is used to control the information, and inputs h t-1 and x t are used to filter the values that should be remembered in a manner similar to the forget gate. Then, using the tanh function, which outputs values ranging from -1 to +1, a vector is generated that contains all possible values for h t-1 and x t. To get the useful information, atlas, the vector's values and the regulated values are multiplied.
3) *Gate at Output:* Output gates are responsible for removing pertinent information from the current cell state and presenting it as an output. The tanh function is first used to the cell to create a vector. The sigmoid function is then used to control the information, and inputs h t1 and x t are used to filter the values to be remembered. Atlast, To send the values as an output and input to the following cell, the vector's values and the controlled values are multiplied.

V. RESULTS

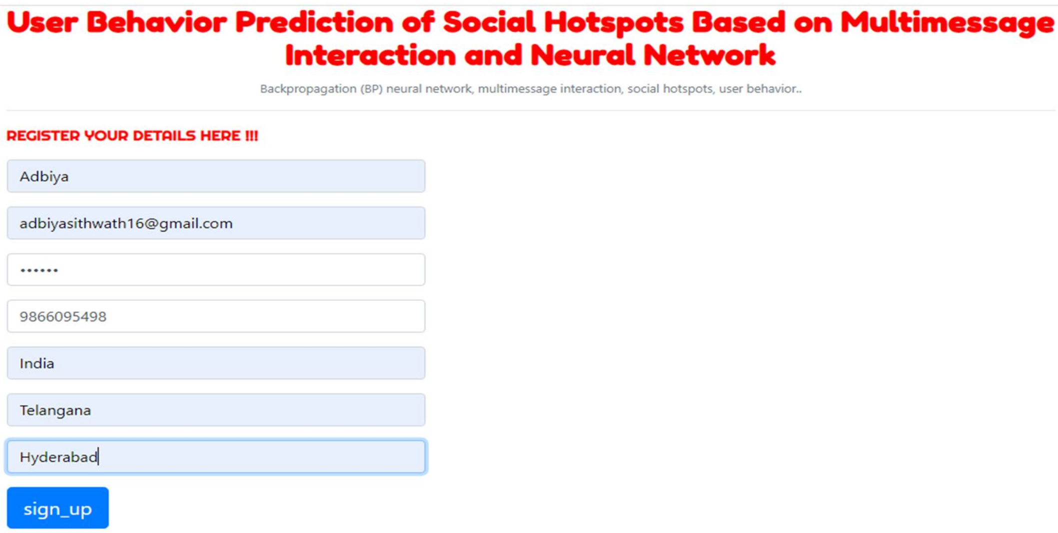
A. Tweeter's Home Page



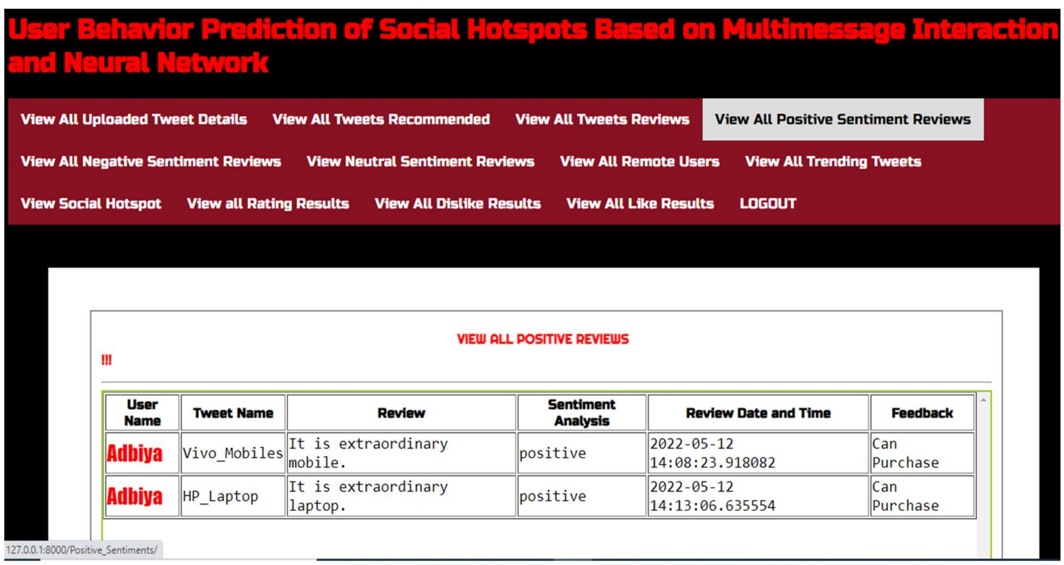
B. Home Page for the Service Provider



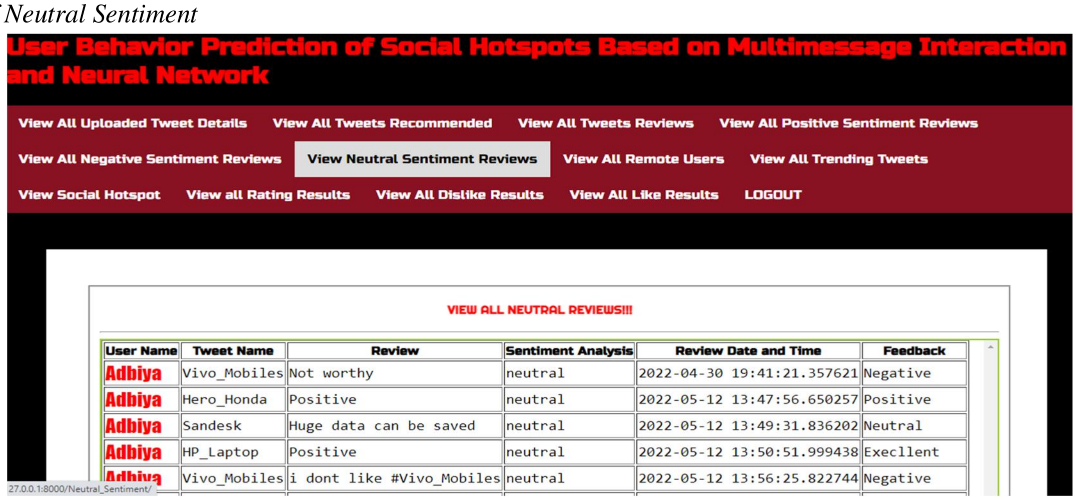
C. Page for User Registration



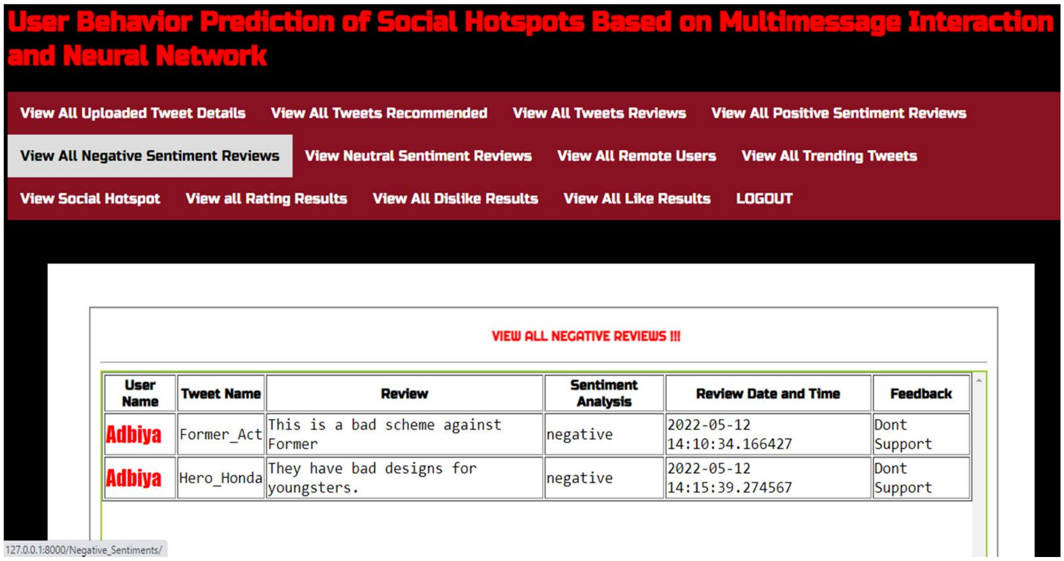
D. Analysis of Positive Sentiment



E. Analysis of Neutral Sentiment



F. Analysis of Negative Sentiment



VI. CONCLUSION

The driving mechanisms of both the user and the multimessage interaction were extracted from the user behaviour data and the basic information data of multiple messages under a hot topic being discussed on a social network, and a prediction model of the user's participation behaviour in the discussed topic was proposed. The computation findings properly depicted the impact of the trending subject on user participation behaviours and quantified the mutual effect strength between the different messages. The suggested strategy was experimentally tested using multimessage data and a popular social media topic.

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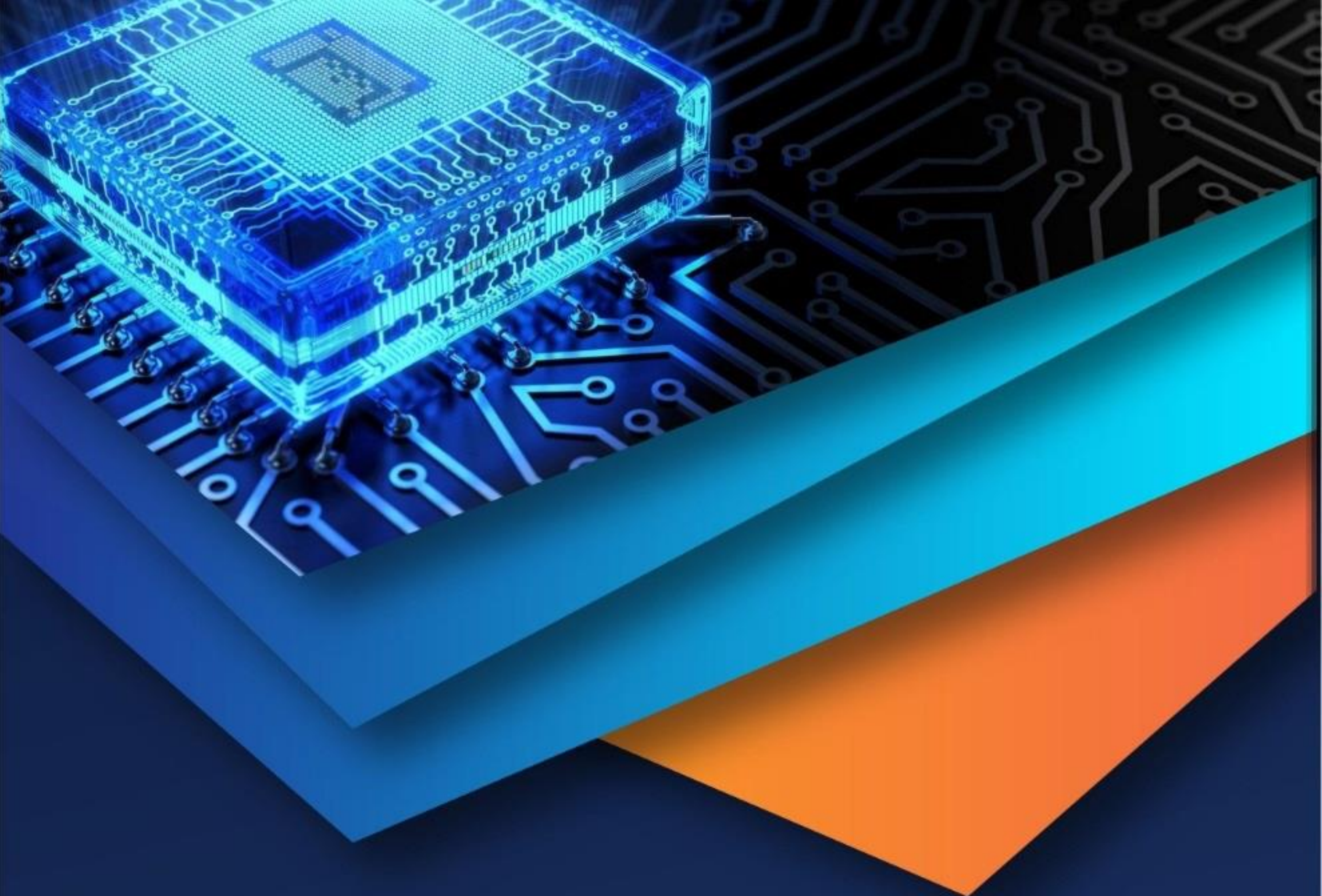

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