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Prediction of Stress and Mood using Neural Network, LSTM and Transfer learning

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Abstract: Stress can be a feeling of emotional or physical tension. It can come from any thought or event that makes you feel frustrated, disturbed, angry or nervous. It also affect the mood of the person. This study is conducting to predict the stress and mood based on heart rate variability which can be collected using Fitbit devices or Apple watches nowadays. In this work SWELL dataset available from the Kaggle repository is used. Neural Network and LSTM is used to predict the stress and mood. Predicting the stress is considered as first task and as mood prediction as second task. For second task prediction, the model created for first task is reused as pretrained model where we make use of transfer learning.
Keywords: Deep Neural Network, LSTM, Transfer Learning.

I. INTRODUCTION

Stress is a sense or feeling of emotional or physical tension. It can come from any event or thought that makes you're feeling frustrated, disturbed, angry, or nervous. Stress causes chemical changes within the body which will raise vital signs, pulse, and blood glucose levels, blood pressure levels, etc.
Some of the causes of stress can be:

A. Being under a lot of pressure
B. Worrying about something
C. Facing big changes

Psychological and emotional signs of stress:
1) Depression or anxiety
2) Anger
3) Irritability
4) Trouble sleeping
5) Feeling unmotivated or unfocused

Stress increases the likelihood of depression, stroke, attack, and asystole.
Stress is usually recognized as a state during which a private is predicted to perform an excessive amount under sheer pressure and during which he/she can only marginally deal with the stress. The mood is defined as a short lived state of mind or feeling.

II. RELATED WORKS

Sara Taylor et.al.[1] proposed Personalized Multitask Learning for Predicting Tomorrow's Mood, Stress, and Health. Employed Multitask Learning (MTL) techniques to coach personalized ML models which are customized to the requirements of every individual, but still leverage data from across the population. Three formulations of MTL are compared: i) MTL deep neural networks, which share several hidden layers but have final layers unique to every task; ii) Multi-task Multi-Kernel learning, which feeds information across tasks through kernel weights on feature types; and iii) a Hierarchical Bayesian model during which tasks share a standard Dirichlet Process prior. These techniques are investigated within the context of predicting future mood, stress, and health using data collected from surveys, wearable sensors, smartphone logs, and therefore the weather. Empirical results demonstrate that using MTL to account for individual differences provides large performance improvements over traditional machine learning methods and provides personalized, actionable insights.
Ahmad Rauf Subhani et.al.[2] proposed Machine Learning Framework for the Detection of Mental Stress at Multiple Levels. Stress is usually recognized as a state during which a private is predicted to perform an excessive amount under sheer pressure and during which he/she can only marginally deal with the stress.

Mental stress has become a social issue and will become a explanation for functional disability during routine work. Stress increases the likelihood of depression, stroke, attack , and asystole . In this paper, a machine learning (ML) framework involving electroencephalogram (EEG) signal analysis of stressed participants is proposed. The proposed ML framework involved EEG feature extraction, feature selection (receiver operating characterisic function, t-test, and therefore the Bhattacharya distance), classification (logistic regression, support vector machine, and naive Bayes classifiers), and tenfold cross-validation.

Natasha Jaques et.al.[3] proposed Multi-task, Multi-Kernel Learning for Estimating Individual Wellbeing. Depression may be a widespread and high problem, disproportionately affecting college-aged individuals. The ability to handle negative life events without becoming depressed, termed resilience, depends on several factors associated with overall wellbeing; these include social support, engagement with work, happiness, physical health, and sleep. For this, they made use of a dataset SNAPSHOT: Sleep, Networks, Affect, Performance, Stress, and Health using Objective Techniques. Multi-task Multi-Kernel Learning (MTMKL) is applied to the matter of modeling students' wellbeing. Because wellbeing may be a complex internal state consisting of several related dimensions, Multi-task learning are often wont to classify them simultaneously. Multiple Kernel Learning is employed to efficiently combine data from multiple modalities.

Rui Xia et. al.[4] proposed A Multi-Task Learning Framework for Emotion Recognition Using 2D Continuous Space. In this study, the focus is on speech-based emotion recognition. In this work, they propose multi-task learning to leverage activation and valence information for acoustic emotion recognition supported the deep belief network (DBN) framework. The categorical emotion recognition task is treated because the major task. For the secondary task, leverage activation and valence labels in two alternative ways , category level-based classification, and continuous level-based regression. The combination of the loss functions from the main and secondary tasks is employed because the objective function within the multi-task learning framework. The DBN is trained to simultaneously optimize the classification performance for the main emotion classification task and this secondary task. The DBN system is learned to lower the regression error of the secondary task while minimizing the classification error of the main task.

Saskia Koldijk et.al.[5] proposed Detecting Work Stress in Offices by Combining Unobtrusive Sensors. The focus of this paper is on developing automatic classifiers to infer working conditions and stress-related mental states from a multimodal set of sensor data (computer logging, facial expressions, posture, and physiology). This paper address two methodological and applied machine learning challenges: One is Detecting work stress using several (physically) unobtrusive sensors, and the second Taking into account individual differences. A comparison of several classification approaches showed that, for the SWELL-KW dataset, neutral and stressful working conditions can be distinguished with 90 percent accuracy by means of SVM. Posture yields the most valuable information, followed by facial expressions. Furthermore, it found that the subjective variable 'mental effort' are often better predicted from sensor data than, e.g., 'perceived stress'.

Yu Zhu et.al.[6] proposed Automated Depression Diagnosis supported Deep Networks to Encode Facial Appearance and Dynamics. In this paper, the study focus on the problem of automatic diagnosis of depression. A new approach to predict the Beck Depression Inventory-II (BDI-II) values from video data are proposed based on the deep networks. The proposed framework is meant during a two-stream manner, aiming at capturing both the facial appearance and dynamics. By employ joint tuning layers that can implicitly integrate the appearance and dynamic information. Experiments are conducted on two depression databases, AVEC2013, and AVEC2014. This paper studies depression recognition and proposes a new approach to model the facial appearance and dynamics, based on deep convolutional neural networks (DCNN). The approach is meant during a two-stream manner, combined with joint-tuning layers for depression prediction. Specifically, facial appearance representation is modeled through a really deep neural network, using face frames because the input. Facial dynamics are modeled by another deep neural network, with face "flow images" as the input. Face "flow images" are generated by computing within the video sub-volumes using the optical flow, to capture facial motions. The two deep networks are then integrated by joint-tuning layers into one deep network, which may further improve the general performance.

Pouneh Soleimaninejadian et.al.[7] proposed Mood Detection and Prediction supported User Daily Activities. Studies show that mood states influence our lifestyle quality and activities, and this is often not the sole way around. Mood also changes because of how we spend our days. In this study data on users' daily lives (known as lifelogging) to both detect and predict their mood is used. The states of mood in this paper are based on Thayer's two-dimensional model of mood. This is the first research to analyze in-depth the physical data collected in lifelogging and its link to determinants and effects of mood including biometrics, physical activities, sleep quality, diet, and user's environment.

Han Yu et.al.[8] proposed Personalized Wellbeing Prediction using Behavioral, Physiological, and Weather Data. The work built and compared several machine learning models to predict future self-reported wellbeing labels (of mood, health, and stress) for the next day and for up to 7 days in the future, using multi-modal data.

The data are from surveys, wearables, mobile phones, and weather information collected during a study from college students, each providing daily data for 30 or 90 days and compared the performance of multiple models, including personalized multi-task models and deep learning models.

S. Dhananjay Kumar et.al.[9] proposed Prediction of Depression from EEG Signal using Long Short Term Memory(LSTM). Depression, a nervous disorder is that the leading explanation for disability worldwide. EEG recordings have found wide use in the diagnosis and analysis of various neurological disorders including depression. In this paper, LSTM (Long-short term memory) deep learning models are utilized in the prediction of trends of depression for subsequent time instants, supported by the features extracted. The statistical time-domain feature encompassing the mean of the amplitude of the data is extracted employing moving window segmentation from the acquired EEG signals. The model uses one LSTM layer with 10 hidden neurons for the prediction. Out of a total of 7000 mean values calculated from a sample of 30 patient records from each resting state, 5600 sample means were used to train the model. The proposed LSTM network could predict the next 1400 sample mean values accurately with a root mean square error of 0.000064.

Sadari Jayawardena et.al.[10] proposed Support Vector Ordinal Regression for Depression Severity Prediction. There has been significant research in automatic depression prediction in recent years thanks to deficiencies in current diagnostic methods. Thus far, depression severity is predicted either as a classification or regression task ignoring the ordinality of depression scores. This paper highlights the importance of using ordinal regression algorithms for ordinal response data by comparing with multiclass classification and regression using a support vector framework. This study has compared ordinal regression (RankSVM) with multiclass classification and regression for depression score prediction using two synthetic datasets and the DAICWOZ depressed speech database.

Ji-won Baek et. al.[11] proposed Context Deep Neural Network Model for Predicting Depression Risk Using multiple correlation . This study proposes the context-DNN model for predicting depression risk using multiple-regression. The context of the proposed model context DNN consists of the knowledge to predict situations and environments influencing depression in consideration of context information. Each context information related to predictor variables of depression becomes an input of DNN, and variable for depression prediction becomes an output of DNN. For DNN connection, the multivariate analysis to predict the danger of depression is employed so on predict the potential context influencing the danger of depression. According to the performance evaluation, the proposed model was evaluated to possess the simplest performance in multivariate analysis and comparative analysis with DNN.

Walter Gerych et.al.[12] proposed Classifying Depression in Imbalanced Datasets using an Autoencoder-Based Anomaly Detection Approach. Untreated depression can significantly decrease quality of life, physical health. The traditional method of diagnosing depression requires the patient to reply to medical questionnaires and is subjective. In this work, anomaly detection methods as a way for mitigating class imbalance for depression detection is explored. The approach adopts a multi-stage machine learning pipeline. First, using autoencoders, project the mobility features of the bulk class (undepressed users). Thereafter, the trained autoencoder then classifies a test set of users as either depressed (anomalous) or not depressed (inliers) employing a One-Class SVM algorithm. The method, when applied to the real-world StudentLife data set shows that even with a particularly imbalanced dataset, this method is in a position to detect individuals with depression symptoms with an AUC-ROC of 0.92, significantly outperforming traditional machine learning classification approaches.

Natasha Jaques et.al.[13] proposed Predicting students' happiness from physiology, phone, mobility, and behavioral data. In order to model students' happiness, applied machine learning methods to data collected from undergraduate students monitored over the amount of 1 month each. The data collected include physiological signals, location, smartphone logs, and survey responses to behavioral questions of undergraduate students. Each day, participants reported their well-being on measures including stress, health, and happiness. Because of the connection between happiness and depression, modeling happiness may help us to detect individuals who are in danger of depression and guide interventions to assist them. This work is additionally curious about how behavioral factors (such as sleep and social activity) affect happiness positively and negatively. A variety of machine learning and have selection techniques are compared.

III. METHOOLOGY

A. Data Collection

SWELL[14][16] dataset used in this work. The SWELL knowledge work (SWELL-KW) dataset was collected by researchers at the Institute for Computing and knowledge Sciences at Radboud University. It is a result of experiments conducted on 25 subjects doing typical office work (for example writing reports, making presentations, reading e-mail, and searching for information). The subject went through typical working stressors such as receiving unexpected email interruptions and pressure to complete their work on a tight schedule. The experiment recorded various data including computer logging, countenance , body postures, ECG signal, and skin conductance. Each participant went through three different working conditions:

1) *No Stress:* the subjects are allowed to work on the tasks as long as they needed for a maximum of 45 minutes but they are not aware of the maximum duration of their tasks.
2) *Time Pressure (Mild Stress):* during this time, the time to finish the task was reduced to 2/3 of the time the participant took in the "no stress" condition.
3) *Interruption (Severe Stress):* the participants received eight emails in the middle of their assigned tasks.

Some emails were relevant to their tasks —and the participant was requested to take specific actions—while others were just irrelevant to their tasks. The experiment lasted for about 3 hours for each subject.

Heart rate variability(HRV) consists of changes within the time intervals between consecutive heartbeats called interbeat intervals. The oscillations of a healthy pulse are complex and constantly changing. HRV is that the fluctuation within the time intervals between adjacent heartbeats. Time-domain indices quantify the quantity of HRV observed during monitoring periods which will range from ~2min to 24h or quantify the quantity of variability in measurements of the interbeat interval, which is that the period of time between successive heartbeats. Frequency domain values calculate the absolute or relative amount of signal energy within component bands or estimate the duration of absolute or relative power into four frequency bands UHF, VHF, LF, HF.

a) UHF - Ultra-low frequency
b) VLF - Very low frequency
c) LF - Low frequency
d) HF - High frequency

HRV reflects the regulation of autonomic balance, vital sign , gas exchange, heart, and vascular tone which refers to the diameter of the blood vessels that regulate vital sign .

B. Transfer learning

Transfer learning used in machine learning, which is the reuse of a pre-trained model on a new problem.With transfer learning, the model will try to exploit what has been learned in one task to improve generalization in another by transfering the weights that the network has learned at "task 1" to a new "task 2." Here the task 1 will be stress prediction and task 2 will be mood prdiction. The general idea is to use the knowledge a model has learned from a task with a lot of available labeled training data in a new task that doesn't have much data. Instead of starting the learning process from scratch, start with patterns learned from solving a related task. Transfer learning's main advantages are saving training time, better performance of neural networks, and not needing a lot of data. Transfer learning can be used in the following cases:

1) There isn't enough labeled training data to train your network from scratch.
2) There already exists a network that is pre-trained on a similar task, which is usually trained on massive amounts of data.
3) When task 1 and task 2 have the same input.

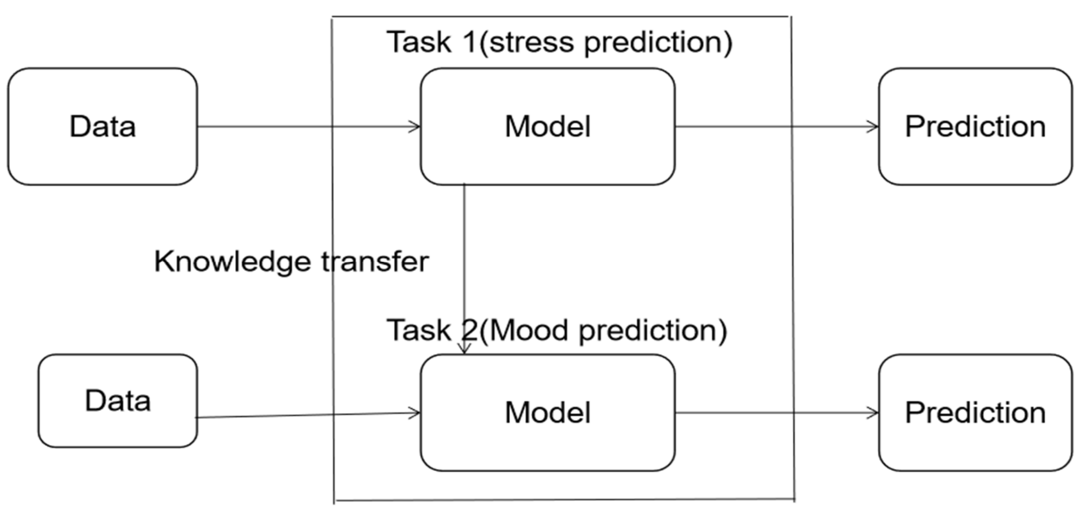

Fig. 1 Idea of Transfer Learning

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IV. CLASSIFICATION MODELS

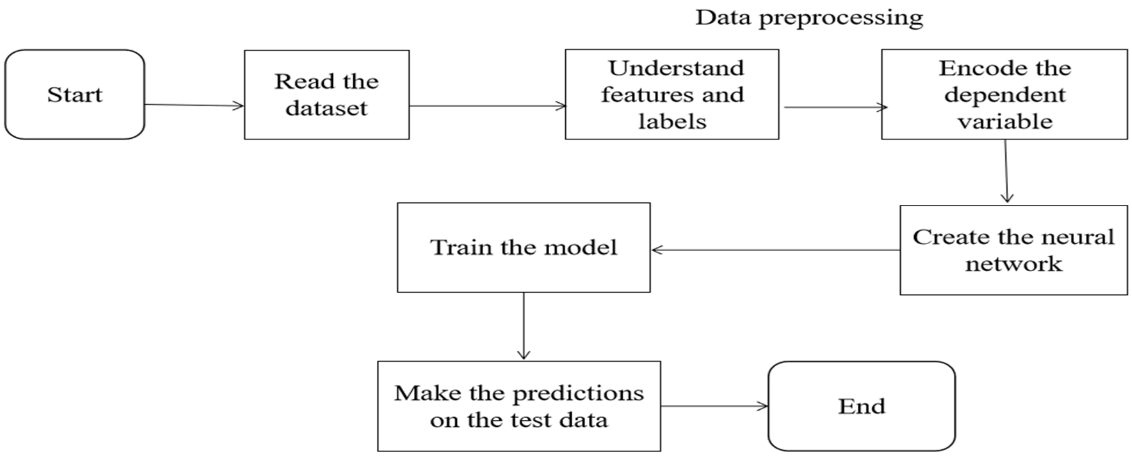

Fig 2. Overall Design

A. Deep Neural Network(DNN)

A deep neural network (DNN) is an artificial neural network (ANN) with multiple hidden layers between the input and output layers. DNNs are typically feedforward networks in which data flows from the input layer to the output layer without forming a circle. At first, the DNN creates a map of virtual neurons and assigns random numerical values as "weights", to connections between them. The weights and inputs are multiplied and return an output between 0 and 1. If the network did not accurately recognize a particular pattern, an algorithm will adjust the weights. That way the algorithm can make some parameters more influential, until it determines the correct mathematical manipulation to fully process the data[15].

In our work, two hidden layers are used with input and output layers. Activation functions used are ReLU and Softmax. The rectified linear activation function or ReLU[17] for short is a piecewise linear function that will output the input directly if it is positive, otherwise, it will output zero. It has become the default activation function for many types of neural networks, it is easier to train and often achieves better performance. Softmax[18] is a mathematical function that converts a vector of numbers into a vector of probabilities, where the probabilities of each value are proportional to the relative scale of each value in the vector. Softmax is the only activation function recommended to use with the categorical cross-entropy loss function[19]. As loss function, categorical cross-entropy is used. Categorical cross-entropy is a loss function that is used in multi-class classification tasks. Adam optimizer is used for optimization. The Adam optimization algorithm is an extension to stochastic gradient descent that has recently seen broader adoption for deep learning applications. Adam is an optimization algorithm that can be used instead of the classical stochastic gradient descent procedure to update network weights iterative based on training data[20]. In our work first a DNN is created to learn the stress prediction task and then reusing the model mood prediction is done.

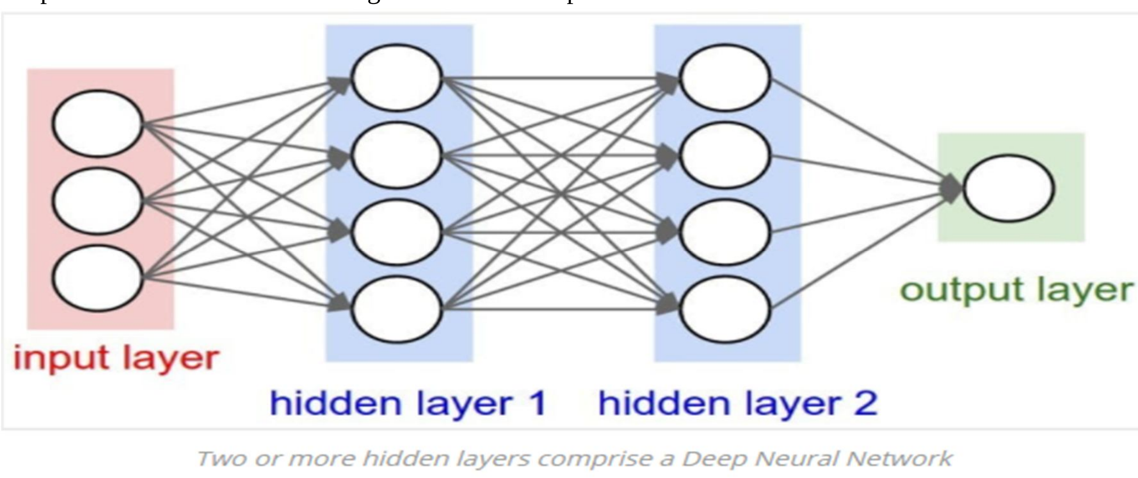

Fig. 3 Deep Neural Network

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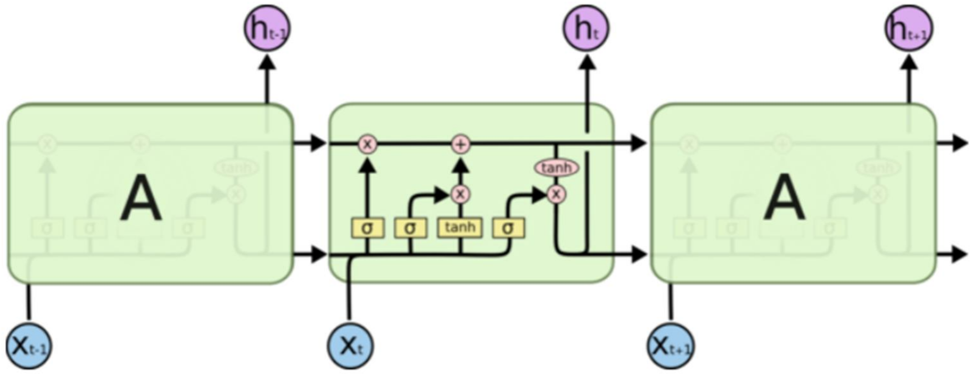

Fig.4 LSTM

B. Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) networks are a type of recurrent neural network capable of learning order dependence in sequence prediction problems. LSTMs are a complex area of deep learning. LSTMs also have a chain like structure, but the repeating module has a different structure from RNN. Instead of having a single neural network layer, there are four, interacting in a very special way. The key to LSTMs is the cell state. The LSTM does have the ability to remove or add information to the cell state, carefully regulated by structures called gates. Gates are a way to optionally let information through. They are composed out of a sigmoid neural net layer and a pointwise multiplication operation. The sigmoid layer outputs numbers between zero and one, describing how much of each component should be let through. A value of zero means “let nothing through,” while a value of one means “let everything through!”. An LSTM has three of these gates, to protect and control the cell state[24]. In our work first a LSTM is created to learn the stress prediction task and then reusing the model mood prediction is done.

V. EVALUATION

The measures using which the performance of the used models are discussed here.

The Accuracy metric calculates the accuracy rate provided by all predictions. A Classification model is first trained using a number of data and tested using some other data.

In our case, we have trained our model using 310000 rows of data and tested or validated using 78000 rows of data. The validation accuracy metric provides the percentage of data which was classified correctly. It gives us the percentage of datas (out of 5000) which was correctly classified(normal/failed)

Precision means the percentage of your results which are relevant. On the other hand, recall refers to the percentage of total relevant results correctly classified by your algorithm.

Precision(P) is another evaluation metric which gives the percentage of our results which are actually relevant. Another metric, Recall(R) means the percentage of total results which are relevant correctly classified. We can say that,

Precision(P) = True positives / (True Positives + False Positives)

Recall(R) = True positives / (True Positives + False Negatives)

Precision gives the percentage of images which are predicted to be in one class, actually belong to that class. Recall specifies, what percentage of images belonging to a class was correctly identified.

TABLE 4

Performance comparison of DNN and LSTM

Model	Accuracy(	Precision	Recall
Stress DNN	99.29	0.66	0.82
Mood DNN	97	0.63	0.76
Stress LSTM	97.95	0.757	0.821
Mood LSTM	98.5	O.74	0.735

VI. CONCLUSION

Two different models developed for predicting the stress and mood. Models for classifying stress in multiple levels as no stress, mild stress, severe stress and mood as happy, sad, or angry was successfully developed. They were trained and tested on the dataset and all of them provided appreciable results. The best result was produces by the LSTM.

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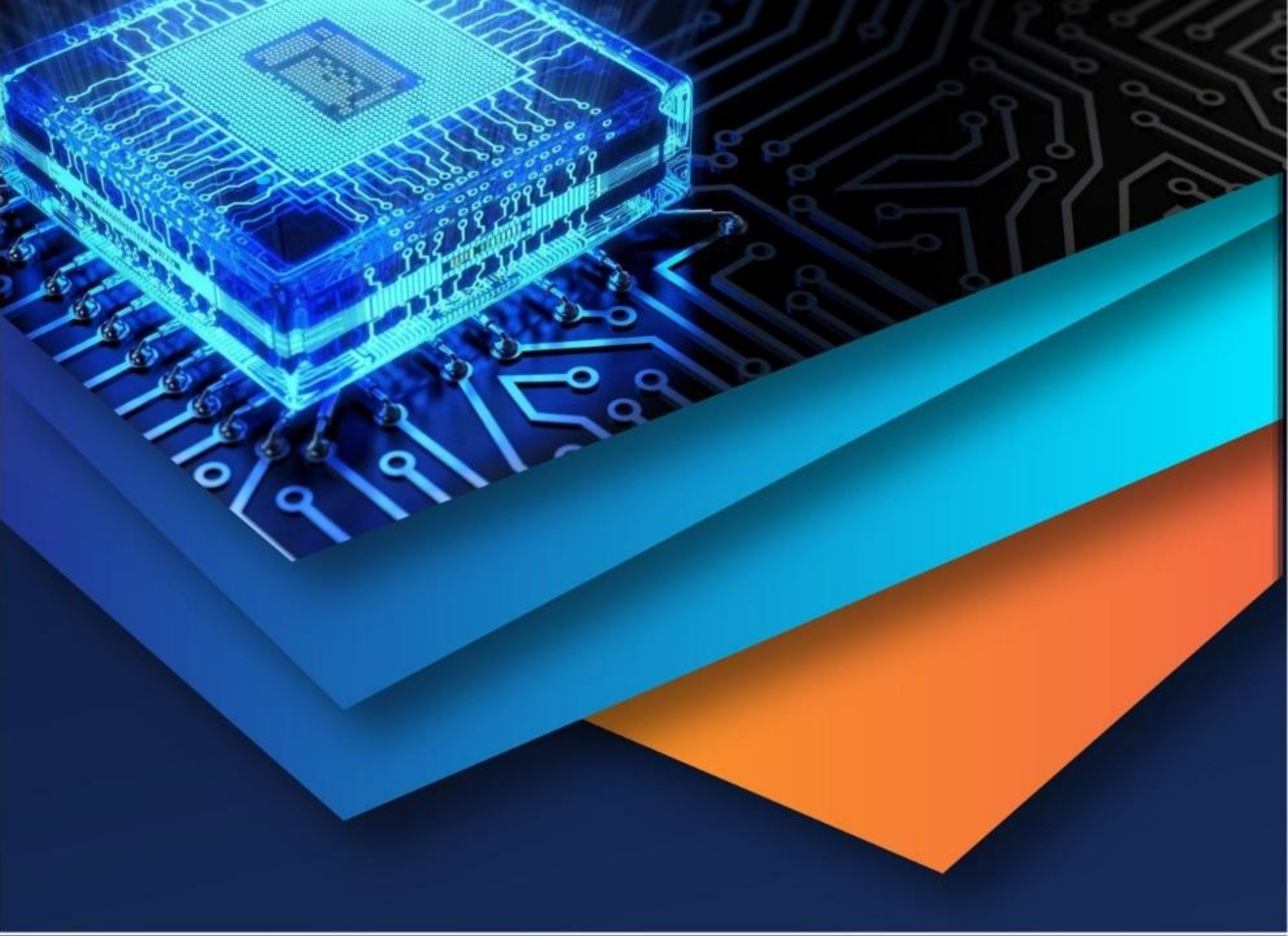

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