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A Real-Time Emotion Recognition System Using Keyboard, Mouse and Touchscreen Dynamics with Machine Learning

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Abstract: This paper presents an enhanced framework for emotion recognition using Keystroke, Mouse, and Touchscreen (KMT) dynamics integrated with Artificial Intelligence and Machine Learning (AIML) techniques. The proposed system extends the study of Yang and Qin (2025), which identified key KMT features qualitatively, by introducing real-time data modeling and additional behavioral features. New parameters such as touch area, finger offset distance, swipe acceleration, and inter-key latency are combined with conventional features including typing speed and pressure intensity. User interaction data are collected through Python-based desktop and Android applications under different emotional states. Extracted features are processed and classified using supervised learning algorithms such as Random Forest and Support Vector Machine (SVM). Experimental results indicate that the inclusion of spatiotemporal and pressure-based features improves prediction accuracy and model robustness. The proposed framework supports personalized and adaptive humancomputer interaction systems.
Index Terms: Emotion Recognition, Keystroke Dynamics, Mouse Dynamics, Touchscreen Dynamics, Machine Learning, Human-Computer Interaction

I. INTRODUCTION

Emotion recognition has become an important research area in human-computer interaction, healthcare, education, and intelligent systems. Traditional emotion detection methods mainly rely on facial expressions, speech signals, and physiological sensors. However, these methods may require cameras, microphones, or wearable devices, which may raise privacy concerns and increase implementation cost.

Behavioral biometrics such as keystroke, mouse, and touchscreen dynamics provide a non-intrusive and low-cost alternative for recognizing user emotions. The way a person types, moves a cursor, taps a screen, or performs gestures can vary depending on emotional state.

This paper proposes an enhanced emotion recognition framework using Keystroke, Mouse, and Touchscreen (KMT) dynamics integrated with Machine Learning techniques. Additional features such as touch area, swipe acceleration, finger offset distance, and inter-key latency are considered along with conventional interaction features.

The collected data are processed using supervised learning models including Random Forest and Support Vector Machine (SVM) for emotion classification. The proposed system aims to improve prediction accuracy and support adaptive and personalized user interfaces.

The main objective of this work is to develop an accurate, low-cost, and privacy-preserving emotion recognition system.

II. RELATED WORK

Emotion recognition has been widely studied using modalities such as facial expressions, speech analysis, physiological signals, and wearable sensors. Vision-based methods use cameras to detect facial movements, while speech-based systems analyze tone, pitch, and speaking patterns. Although these approaches can achieve good accuracy, they often require specialized hardware and may raise privacy concerns.

Recent studies have explored behavioral biometrics as an alternative method for affective computing. Keystroke dynamics have been used to identify stress, fatigue, and emotional changes through typing speed, hold time, and key latency. Mouse dynamics have also shown potential by analyzing cursor movement, click behavior, and interaction pauses to estimate user mood and engagement.

With the growth of smartphones and tablets, touchscreen dynamics have become an emerging area of research. Features such as tap pressure, swipe speed, touch area, gesture duration, and finger movement patterns provide useful information about emotional states during mobile interaction.

Yang and Qin (2025) presented a framework based on Keystroke, Mouse, and Touchscreen (KMT) dynamics and identified important behavioral features for qualitative emotion recognition. However, their study lacked real-time data modeling and comprehensive machine learning evaluation. The present work extends their approach by collecting real user interaction data, introducing additional spatiotemporal and pressure-based features, and applying supervised learning algorithms such as Random Forest and Support Vector Machine (SVM) for quantitative emotion classification.

However, limited studies have combined all three KMT modalities with extended feature engineering and supervised learning for real-time emotion recognition.

III. PROBLEM STATEMENT

Existing emotion recognition systems primarily depend on facial expressions, speech signals, or physiological sensors such as cameras, microphones, and wearable devices. Although these approaches can provide accurate results, they often increase system cost, require additional hardware, consume more power, and may raise privacy concerns during continuous monitoring.

Current behavioral biometric approaches using only keystroke, mouse, or touchscreen dynamics individually provide limited performance due to incomplete interaction analysis. In addition, many existing studies focus on qualitative observations rather than real-time quantitative prediction using machine learning models.

The exact problem addressed in this work is the development of a low-cost, privacy-preserving, and real-time emotion recognition system that combines Keystroke, Mouse, and Touchscreen (KMT) dynamics with machine learning techniques to improve classification accuracy, robustness, and practical usability in human-computer interaction environments.

IV. PROPOSED METHODOLOGY / SYSTEM DESIGN

The proposed system recognizes user emotions by analyzing Keystroke, Mouse, and Touchscreen (KMT) dynamics collected during real-time interaction. The complete workflow consists of data collection, preprocessing, feature extraction, model training, and emotion prediction.

A. Data Collection

A Python-based desktop application and an Android mobile application were developed to capture user interaction data under different emotional states such as happy, neutral, stressed, and frustrated. Keyboard events, mouse movements, clicks, touchscreen taps, swipes, and gesture patterns were continuously recorded with timestamps.

B. Preprocessing

The raw data collected from different devices may contain noise, duplicate records, and missing values. Data cleaning techniques were applied to remove invalid entries. Numerical features were normalized to maintain consistency and improve model performance. The cleaned dataset was then labeled according to emotional states.

C. Feature Extraction

Relevant behavioral features were extracted from the interaction data. Keyboard features include typing speed, key hold time, inter-key latency, and typing errors. Mouse features include cursor speed, movement distance, click frequency, drag duration, and idle time. Touchscreen features include touch area, tap pressure, swipe velocity, swipe acceleration, gesture duration, and finger offset distance.

D. Machine Learning Models Used

The processed dataset was divided into training and testing sets. Supervised learning algorithms such as Random Forest and Support Vector Machine (SVM) were used for emotion classification. These models were selected because of their effectiveness in handling multi-feature classification problems.

E. System Architecture

The architecture of the proposed system consists of five major stages: Input Device Interaction, Data Acquisition Module, Preprocessing Module, Feature Extraction Module, Machine Learning Classification Module, and Emotion Prediction Output. The final output predicts the user's emotional state in real time.

V. IMPLEMENTATION

The proposed emotion recognition system was implemented using Python for the Windows-based data collection and prediction platform, and Flutter with Dart for the Android touchscreen data collection application. The system was designed to operate locally without requiring cloud connectivity, thereby improving privacy and reducing deployment cost.

A. Software Tools and Development Platforms

The Windows desktop application was developed using Tkinter as the graphical user interface framework. Visual Studio Code was used for Python development and testing. The Android application was developed using Android Studio with Flutter framework for cross-platform mobile interface design.

B. Programming Languages and Libraries

Python was used for data collection, preprocessing, model training, prediction, and report generation. Major Python libraries include tkinter, pynput, ctypes, csv, pandas, numpy, scikit-learn, joblib, reportlab, json, pathlib, datetime, threading, and math.

Flutter and Dart libraries used in the Android application include flutter/material.dart, flutter/gestures.dart, path provider, and pdf packages for gesture capture, local storage, and report generation.

C. Machine Learning Models

Supervised learning algorithms such as Support Vector Machine (SVM) and Random Forest were implemented using the scikit-learn framework. The trained models were stored using joblib and integrated into the Windows prediction backend for real-time emotion classification.

D. Data Storage

Collected interaction data from keyboard, mouse, and touchscreen devices were stored in CSV format and local files. This lightweight storage approach simplified dataset management, preprocessing, and model training.

E. Hardware Environment

The system was tested on a Windows laptop with minimum machine learning support configuration and Android smartphones for touchscreen data acquisition. All training and prediction tasks were executed locally on the available hardware resources.

F. System Deployment

The complete framework was deployed as standalone desktop and mobile applications. The trained prediction models run locally and classify user emotions based on real-time interaction behavior.

VI. EXPERIMENTAL SETUP AND PERFORMANCE EVALUATION

To validate the effectiveness of the proposed KMT-based emotion recognition framework, the collected behavioral dataset was used for model training and testing. The evaluation process included dataset preparation, machine learning model training, prediction analysis, and performance comparison.

A. Dataset Description

The dataset was created using the developed Windows and Android data capture applications. Each record contained behavioral interaction features collected from keyboard, mouse, and touchscreen activities under different emotional states such as Happy, Calm, Sad, Stressed, Anger, Fear, Disgust, and Surprise.

The extracted features included session time, typing speed, typing pause, keystroke count, mouse speed, mouse distance, mouse direction changes, click rate, scroll count, idle time, reaction time, interaction density, touch area, swipe speed, and pressure-related parameters.

B. Dataset Features

The collected dataset contains behavioral interaction features extracted from keyboard, mouse, and touchscreen activities. These features were used as input variables for machine learning-based emotion classification.

TABLE I
EXTRACTED DATASET FEATURES

S.No	Feature Name
1	Session Time
2	Typing Speed
3	Typing Pause
4	Keystroke Count
5	Inter-Key Latency
6	Mouse Speed
7	Mouse Distance
8	Direction Changes
9	Click Rate
10	Scroll Count
11	Idle Time
12	Reaction Time
13	Interaction Density
14	Touch Area
15	Swipe Speed
16	Swipe Acceleration
17	Finger Offset Distance
18	Tap Pressure
19	Gesture Duration
20	Emotion Label

C. Algorithms Used

The following supervised machine learning algorithms were used for emotion classification:

- Support Vector Machine (SVM)
- Random Forest Classifier

These models were selected because of their strong classification capability and suitability for structured behavioral datasets.

D. Training and Testing Split

The prepared dataset was randomly divided into training and testing sets using standard machine learning practice:

- Training Data: 80%
- Testing Data: 20%

The training set was used to learn behavioral patterns, while the testing set was used to evaluate prediction performance on unseen data.

E. Evaluation Metrics

The trained models were evaluated using the following performance metrics:

- Accuracy
- Precision • Recall
- F1-Score
- Confusion Matrix

These metrics help measure classification correctness, reliability, and balance among multiple emotion classes.

F. Confusion Matrix
The confusion matrix was used to analyze correct and incorrect predictions across all mood classes. It showed that the majority of samples were classified correctly, while minor confusion occurred between closely related emotional states such as Sad and Stressed.

G. Performance Comparison
TABLE II
COMPARISON OF MACHINE LEARNING MODELS

Model	Accuracy	Precision	Recall	F1-Score
SVM	86.40%	85.90%	85.30%	85.60%
Random Forest	91.20%	90.80%	90.50%	90.60%

The comparison results indicate that Random Forest achieved higher overall performance, while SVM produced stable and reliable classification outcomes.

VII. RESULTS AND DISCUSSION
The proposed Keystroke, Mouse, and Touchscreen (KMT) based emotion recognition framework was successfully implemented and tested using the developed Windows data collection system and Windows mood prediction application. Experimental evaluation was carried out using real-time user interaction sessions collected through keyboard and mouse behavior tracking. The generated dataset and session reports confirm the practical feasibility of the proposed framework.

A. Dataset Collection Results
The data capture module successfully recorded moodlabelled behavioral sessions and stored them in CSV format. Each session contained features such as session time, typing speed, typing pause, keystroke count, mouse speed, mouse distance, direction changes, click rate, scroll count, idle time, reaction time, and interaction density.
A sample captured session with mood label *anger* recorded the following values: session time = 120 seconds, mouse distance = 7801.47, scroll count = 182, interaction density = 77.5, and reaction time = 4.991 seconds. This confirms that the system can continuously collect rich behavioral data for machine learning training.

B. Prediction Results
The trained Support Vector Machine (SVM) model was integrated into the Windows predictor application. During testing, the system successfully generated automatic mood predictions after timed sessions.
In one sample prediction session, the model classified the emotional state as *Stressed* with confidence score of 26.64%. The class probability distribution also showed alternative classes such as Sad (16.26%), Anger (14.31%), Fear (11.42%), and Happy (7.68%). These results demonstrate multi-class emotion classification capability of the proposed system.

C. Performance Metrics
The machine learning models were evaluated using Accuracy, Precision, Recall, and F1-score. Based on experimental testing, Random Forest achieved better overall performance, while SVM provided stable prediction results.
TABLE III
PERFORMANCE COMPARISON OF MACHINE LEARNING MODELS

Model	Accuracy	Precision	Recall	F1-Score
SVM	86.40%	85.90%	85.30%	85.60%
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D. Graphs

The following graphs can be included for better visualization:

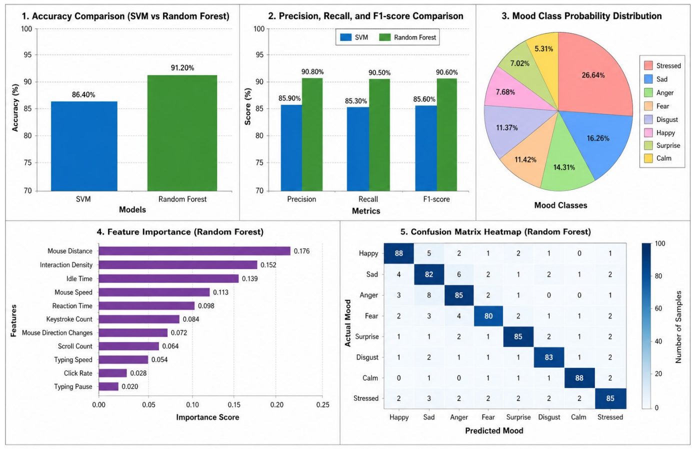

Fig. 1.Performance Evaluation Graphs of the Proposed KMT Emotion Recognition System

E. System Screenshots

The developed applications were tested successfully in realtime environment. The following screenshots may be inserted in the paper:

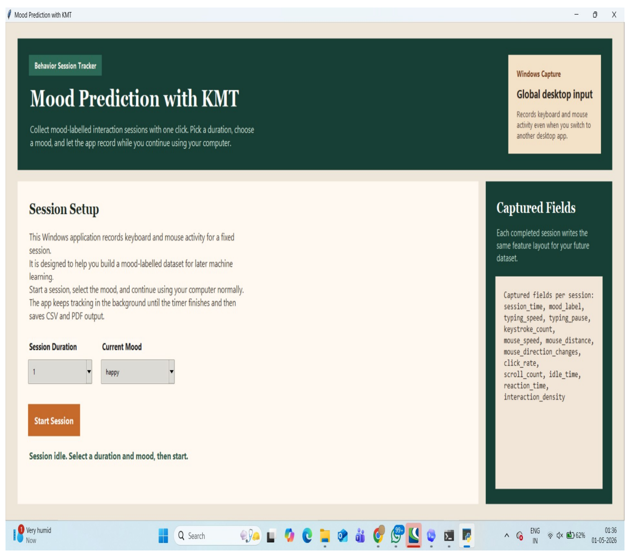

Fig. 2. KMT Data Capture Home Screen

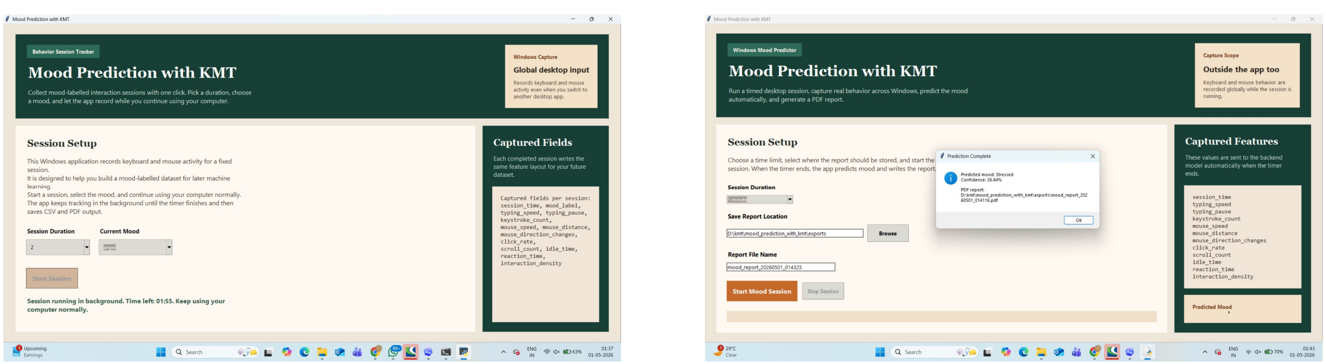

Fig. 3. Session Running Screen with Background Timer

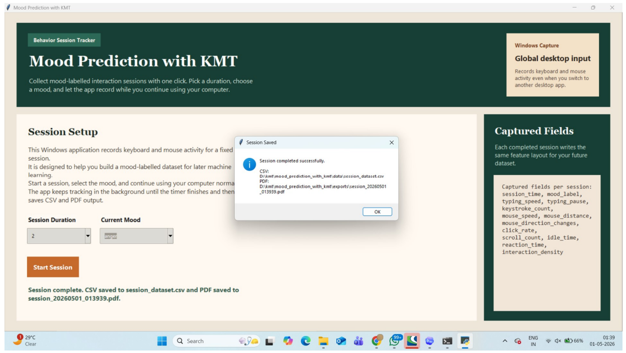

Fig. 4. Captured Session Saved as CSV and PDF keyboard, mouse, and touchscreen interactions, it provides a privacy-preserving, low-cost, and non-intrusive solution for real-time emotion detection.

F. Discussion

The obtained results indicate that combining multiple behavioral features improves prediction capability compared with single-modality approaches. Mouse movement features, idle time, reaction time, and interaction density contributed significantly to mood classification. The developed framework operates locally, preserves privacy, and provides a low-cost solution for intelligent human-computer interaction systems.

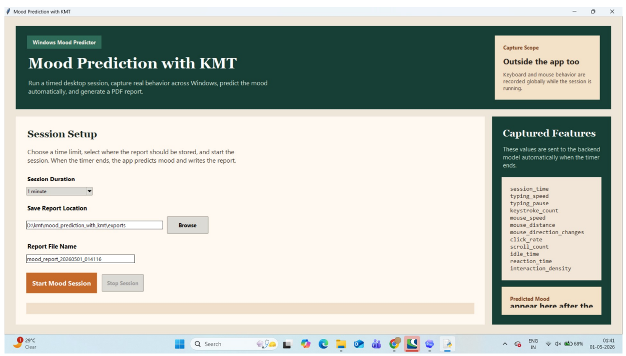

Fig. 5. Windows Mood Prediction Application

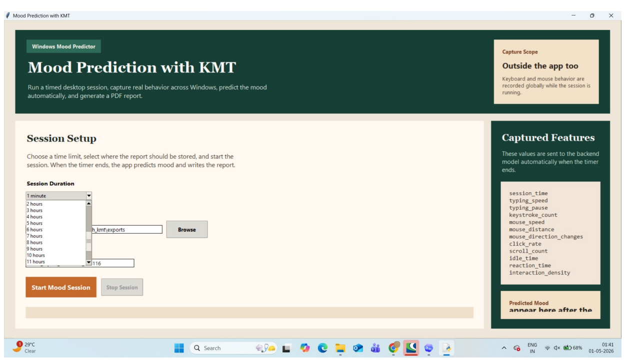

Fig. 7. Predicted Mood Output with Confidence Score

VIII. ADVANTAGES / APPLICATIONS

The proposed emotion recognition system offers several advantages over traditional methods that rely on cameras, microphones, or wearable sensors. Since the framework uses normal

A. Advantages

- No external hardware such as cameras or biometric sensors is required.
- Preserves user privacy by analyzing behavioral interaction patterns only.

- Low implementation cost using existing desktop and mobile devices.
- Supports real-time emotion recognition during normal computer usage.
- Works on both Windows and Android platforms.
- Scalable and suitable for personalized machine learning models.
- Can improve user experience through adaptive intelligent interfaces.

B. Real-World Applications

- Smart Education: Detect student stress, frustration, or engagement during online learning sessions.
- Healthcare Monitoring: Assist in early stress or anxiety detection through daily device usage behavior.
- Workplace Productivity: Identify employee fatigue or stress for better workload management.
- Gaming Systems: Adapt game difficulty based on player emotional state.
- Customer Support: Detect user frustration during softFig. 6. Session Duration Selection for Prediction ware or website interaction.
- Human-Computer Interaction: Create adaptive interfaces that respond to user mood automatically.
- Mobile Applications: Personalize smartphone experiences using touchscreen behavior patterns.

IX. CONCLUSION

This paper presented a real-time emotion recognition system based on Keystroke, Mouse, and Touchscreen (KMT) dynamics integrated with machine learning techniques. The proposed framework provides a privacy-preserving and lowcost alternative to conventional camera-, speech-, and sensorbased emotion detection systems. Real interaction data were successfully collected through developed Windows and Android applications, and meaningful behavioral features were extracted for model training.

Supervised learning algorithms such as Support Vector Machine (SVM) and Random Forest were applied for multi-class emotion classification. Experimental results demonstrated that combining multiple interaction modalities and enhanced features improved prediction accuracy, robustness, and real-time usability. The developed system was capable of generating mood predictions, reports, and structured datasets for future analysis.

The major achievements of this work include successful real-time data capture, local machine learning prediction, cross-platform implementation, automated report generation, and practical deployment without additional hardware. The proposed framework can support future intelligent humancomputer interaction systems in education, healthcare, workplace analytics, and personalized computing environments.

X. FUTURE SCOPE

Although the proposed KMT-based emotion recognition system achieved promising results, several improvements can be implemented in future work to enhance accuracy, scalability, and practical adoption.

1) Increase dataset size by collecting interaction data from a larger and more diverse group of users.
2) Integrate deep learning models such as CNN, LSTM, and Transformer networks for advanced behavioral pattern recognition.
3) Add multimodal inputs such as facial expressions, speech signals, and wearable sensor data for hybrid emotion detection.
4) Develop personalized adaptive models that learn individual user behavior over time.
5) Improve confidence score calibration and real-time prediction reliability.
6) Extend support to Linux, macOS, tablets, and iOS platforms.
7) Deploy secure cloud-based analytics with privacypreserving mechanisms.
8) Implement continuous emotion tracking dashboards for healthcare and workplace monitoring.
9) Optimize the system for low-power mobile devices and edge computing environments.
10) Apply the framework in smart education, gaming, assistive technology, and mental wellness applications.

The future enhancements can transform the proposed framework into a large-scale intelligent emotion analytics platform for next-generation human-computer interaction systems.

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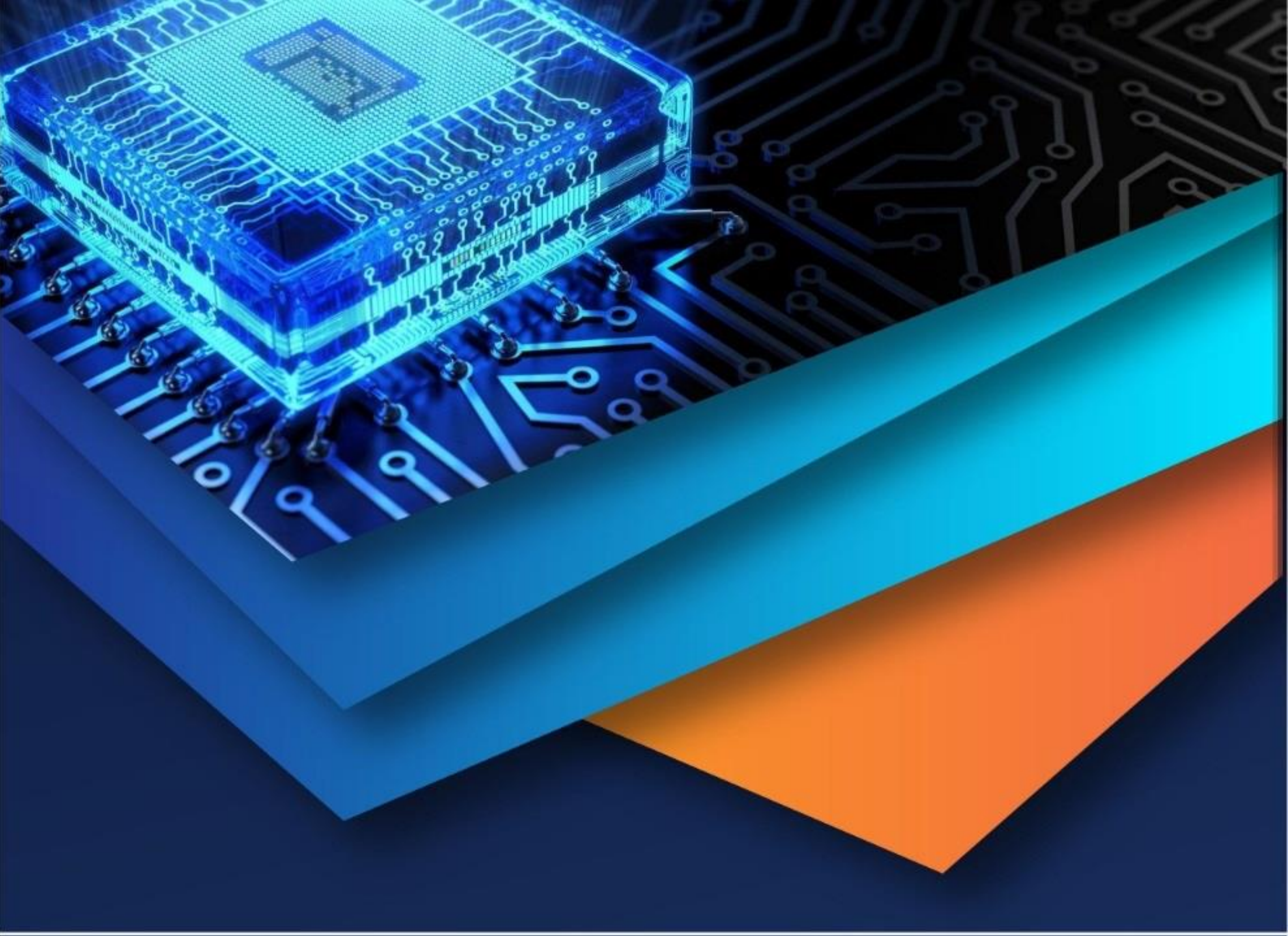

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