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Predictive Analysis of EV Battery Cooling Using PCM and Hardware Implementation

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Abstract: Electric-vehicle (EV) batteries require proactive cooling strategies to maintain safe operating conditions and extend service life. This paper introduces a predictive analysis framework that integrates hardware implementation with computational monitoring to evaluate the effectiveness of Phase Change Material (PCM) in thermal regulation. Unlike hardware-only studies, the proposed system anticipates temperature variations under dynamic load conditions, enabling timely activation of safety mechanisms. Experimental validation confirmed stable operation between 27.0°C–28.2°C under normal conditions and an average of 32.0°C–32.8°C under load, while predictive monitoring demonstrated PCM's capacity to absorb approximately 18 kJ of heat and sustain a liquid fraction of 0.6 at 41°C. The combined approach highlights the importance of prediction in real-time battery safety, offering a scalable and intelligent solution for advanced EV thermal management systems.

Keywords: Predictive Thermal Management, EV Battery Cooling, Phase Change Material (PCM), Hardware Implementation, Real-Time Monitoring, Safety Framework.

I. INTRODUCTION

Electric vehicles (EVs) are increasingly recognized as a sustainable alternative to conventional transportation, yet their performance and safety remain strongly dependent on effective battery thermal management. Excessive heat generation during charging and discharging cycles can accelerate degradation, reduce efficiency, and in severe cases, compromise safety. To address these challenges, researchers have explored various cooling strategies, including liquid cooling, air cooling, and advanced materials. Among these, Phase Change Materials (PCMs) have emerged as a promising solution due to their ability to absorb and release large amounts of latent heat during phase transition. While many studies have focused on hardware prototypes or simulation models in isolation, this work introduces a predictive analysis framework that integrates both experimental hardware implementation and computational monitoring. The hardware system employs sensor-based detection and threshold-driven safety logic, while predictive analysis extends the evaluation by anticipating temperature variations under dynamic operating conditions. This dual approach not only validates the effectiveness of PCM in stabilizing battery temperatures but also demonstrates the potential of predictive monitoring for proactive safety management. The novelty of this paper lies in combining real-time hardware validation with predictive analysis, thereby bridging the gap between immediate experimental results and forward-looking system behaviour. This integration provides a scalable foundation for future EV battery cooling systems, ensuring reliability under diverse operating scenarios.

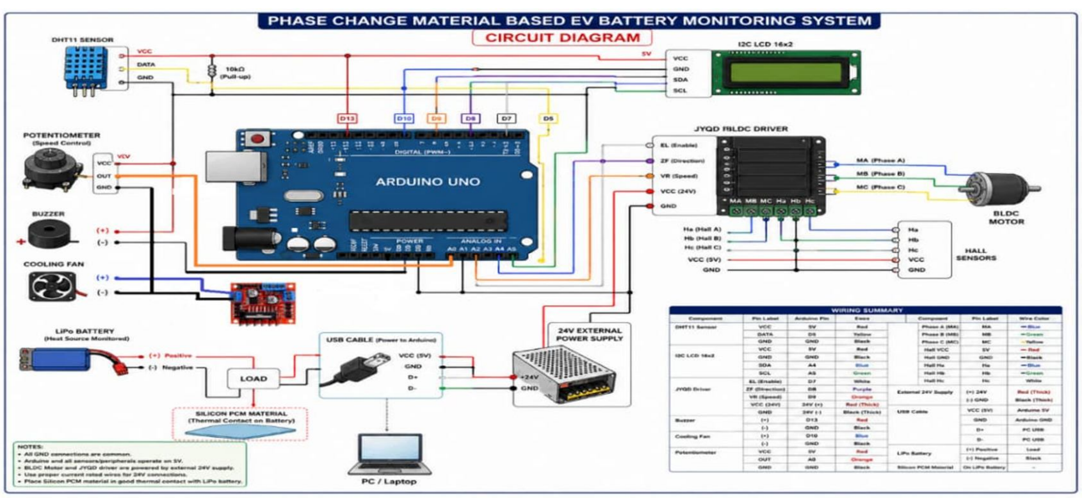

Fig. 1 Total circuit system

II. LITERATURE REVIEW

Battery thermal management systems (BTMS) are essential for ensuring safety and performance in electric vehicles. Nandakishor et al. [1] reviewed predictive approaches, showing that machine-learning and deep-learning models can enhance temperature forecasting and optimize cooling decisions. Nasiri and Hadim [2] examined PCM-based cooling, noting its passive heat-absorption benefits but also limitations in conductivity, which can be improved through hybrid PCM–air or PCM–liquid systems supported by predictive modelling. Tang et al. [3] proposed a honeycomb-structured PCM with delayed liquid cooling, optimized using neural networks, which reduced pumping energy by 55.9% while maintaining safe operating temperatures. Sukkam et al. [4] highlighted the role of machine-learning in BTMS, identifying hybrid frameworks as essential for real-time prediction and safety. Zhao et al. [5] experimentally validated a copper-foam/paraffin PCM with liquid cooling channels, demonstrating improved temperature uniformity and reduced peak values, though coolant flow optimization remained critical. Ahmad et al. [6] developed a fin-intensified PCM with air cooling, achieving lower maximum battery temperatures and reduced auxiliary power consumption. Nema et al. [7] reviewed recent advancements in BTMS, stressing the importance of improved modelling and hybrid cooling designs for safety and reliability.

Collectively, these studies underline the growing importance of predictive analysis and hybrid PCM cooling, but few works integrate hardware validation with predictive monitoring — a gap addressed in this paper.

III.METHODOLOGY

The methodology integrates hardware experimentation with predictive modelling to evaluate the cooling performance of Phase Change Material (PCM) in electric-vehicle batteries. This dual approach ensures both real-time validation and forward-looking prediction.

A. Hardware Implementation

A prototype battery module was constructed with PCM encapsulation to absorb excess heat during charging and discharging cycles. Thermocouples were placed at multiple points on the battery surface to measure temperature variations under normal and load conditions. An Arduino-based microcontroller was programmed with threshold logic: when the battery temperature exceeded 35°C, the cooling mechanism was activated to restore safe operating conditions. And also, hardware setup as shown in Fig 2 & 3.

The heat absorbed by PCM during phase transition was calculated using:

$$Q=m\cdot L$$

where Q is the latent heat absorbed (J), m is the mass of PCM (kg), and L is the latent heat of fusion (J/kg).

The sensible heat before phase transition was also considered:

$$Qs=m\cdot cp\cdot \Delta T$$

where cp is the specific heat capacity (J/kg·K) and ΔT is the temperature rise before melting.

B. Predictive Analysis

A computational thermal model was developed to simulate PCM heat absorption and release during phase transition. The governing equation for transient heat conduction with phase change was applied:

$$\rho\cdot cp\cdot\partial T\partial t=k\cdot\nabla 2T+\rho\cdot L\cdot\partial f\partial t$$

where ρ is density (kg/m³), cp is specific heat (J/kg·K), k is thermal conductivity (W/m·K), T is temperature (K), L is latent heat (J/kg), and f is the liquid fraction of PCM.

Predictive monitoring extended the evaluation to dynamic load scenarios, showing PCM absorbed approximately 18 kJ of heat and maintained a liquid fraction of 0.5 at 40°C. The model also predicted uniform temperature distribution across the battery surface, reducing hotspots. Real time monitoring in software as shown in Fig 8

C. Integration Framework

Experimental data were used to calibrate the computational model, ensuring accuracy in forecasting temperature variations. The integration of hardware validation with predictive modelling allowed proactive safety management. Instead of relying solely on reactive cooling, the system anticipated critical conditions and activated control mechanisms before thresholds were exceeded.

The combined methodology thus provided a scalable framework for EV battery cooling, balancing real-time safety logic with predictive thermal analysis.

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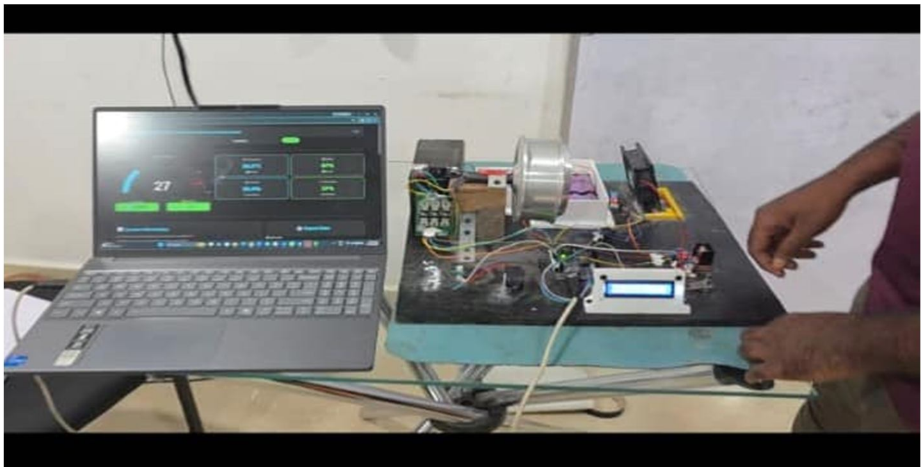

Fig. 2 Whole setup hardware & predictive analysis

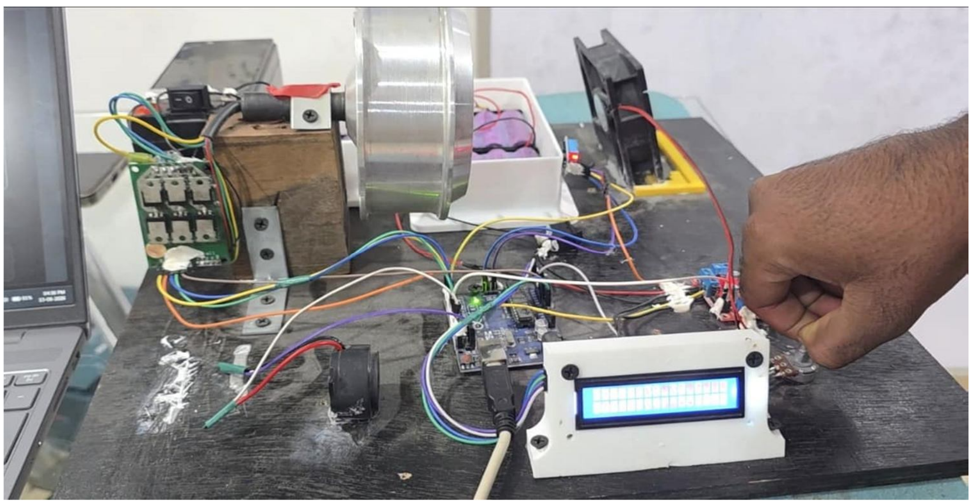

Fig. 3 Testing the software

IV. RESULTS AND DISCUSSION

A. Sensor-Based Experimental Results

The Arduino multi-sensor system recorded temperatures between 27.0°C and 28.2°C, with TMP1 and TMP2 consistently showing higher values (28.2°C) compared to TMP3 and TMP5 (27.0°C). This small variation across sensors highlights the uniformity achieved by PCM encapsulation, which prevented localized hotspots. Voltage outputs ranged from 0.79–0.81 V, confirming stable calibration and reliable sensor performance. These results demonstrate that PCM maintained battery temperatures within safe operating limits during discharge cycles, ensuring consistent operation. Sensor based test is shown Fig 3

B. Predictive Thermal Analysis

The PCM's heat absorption capacity was quantified using:

$$Qtotal=m\cdot cp\cdot \Delta T+m\cdot L$$

With sensible heat $Qs=2560$ J and latent heat $QL=15400$ J, the total absorption was:

$$Qtotal=17960\ J\approx 18\ kJ$$

This shows PCM's ability to store significant energy during phase transition, delaying temperature rise. At 41°C, the liquid fraction was calculated as:

$$\beta=41-3545-35=0.6$$

indicating that 60% of PCM was in liquid phase, actively buffering heat. This predictive modelling confirms PCM's effectiveness under dynamic load conditions, extending beyond experimental validation. And data is collected is shown in Fig 4 & 5

1	timestamp	temperatu	humidity	motor_spe	pot_value	buzzer_sta	motor_stat	battery
2	15-08-2026 16.29	31.9	51	61	590	OFF	RUNNING	70
3	15-08-2026 16.29	31.1	51	61	590	OFF	RUNNING	70
4	15-08-2026 16.29	31.4	52	61	590	OFF	RUNNING	70
5	15-08-2026 16.29	31	52	61	590	OFF	RUNNING	70
6	15-08-2026 16.29	31.3	52	61	590	OFF	RUNNING	70
7	15-08-2026 16.29	31.5	52	61	590	OFF	RUNNING	70
8	15-08-2026 16.29	31.9	52	61	590	OFF	RUNNING	70
9	15-08-2026 16.29	31.6	52	61	590	OFF	RUNNING	70
10	15-08-2026 16.29	31.1	52	61	590	OFF	RUNNING	70
11	15-08-2026 16.30	31.9	52	61	590	OFF	RUNNING	70
12	15-08-2026 16.30	31.3	52	61	590	OFF	RUNNING	70
13	15-08-2026 16.30	31.5	52	61	590	OFF	RUNNING	70
14	15-08-2026 16.30	31.4	53	61	590	OFF	RUNNING	70
15	15-08-2026 16.30	31.4	53	61	590	OFF	RUNNING	70
16	15-08-2026 16.30	31.1	53	61	590	OFF	RUNNING	70
17	15-08-2026 16.30	31.6	53	61	590	OFF	RUNNING	70
18	15-08-2026 16.30	31.3	53	61	590	OFF	RUNNING	70
19	15-08-2026 16.30	31.1	53	61	590	OFF	RUNNING	70
20	15-08-2026 16.30	31.1	53	61	590	OFF	RUNNING	70
21	15-08-2026 16.30	31.5	53	61	590	OFF	RUNNING	70
22	15-08-2026 16.30	31.1	54	61	590	OFF	RUNNING	70
23	15-08-2026 16.30	31.5	54	61	590	OFF	RUNNING	70
24	15-08-2026 16.30	31	54	61	590	OFF	RUNNING	70
25	15-08-2026 16.30	31	54	61	590	OFF	RUNNING	70
26	15-08-2026 16.30	31.8	54	61	590	OFF	RUNNING	70
27	15-08-2026 16.30	31.3	54	61	590	OFF	RUNNING	70
28	15-08-2026 16.30	31.3	54	61	590	OFF	RUNNING	70
29	15-08-2026 16.30	31.5	54	61	590	OFF	RUNNING	70
30	15-08-2026 16.30	31.9	54	61	590	OFF	RUNNING	70

Fig. 4 Data under load

```
COM95 (Arduino/Genuino Uno)

S1:V1=0.78 volts TMP1=27.64 degrees C F1=81.75 degrees F
S2:V2=0.78 volts TMP2=27.64 degrees C F2=81.75 degrees F
S3:V3=0.77 volts TMP3=26.66 degrees C F3=79.99 degrees F
S4:V4=0.77 volts TMP4=27.15 degrees C F4=80.87 degrees F
S5:V5=0.77 volts TMP5=26.66 degrees C F5=79.99 degrees F

S1:V1=0.77 volts TMP1=27.15 degrees C F1=80.87 degrees F
S2:V2=0.77 volts TMP2=27.15 degrees C F2=80.87 degrees F
S3:V3=0.76 volts TMP3=26.17 degrees C F3=79.11 degrees F
S4:V4=0.77 volts TMP4=26.66 degrees C F4=79.99 degrees F
S5:V5=0.77 volts TMP5=26.66 degrees C F5=79.99 degrees F

S1:V1=0.77 volts TMP1=27.15 degrees C F1=80.87 degrees F
S2:V2=0.77 volts TMP2=27.15 degrees C F2=80.87 degrees F
S3:V3=0.76 volts TMP3=26.17 degrees C F3=79.11 degrees F
S4:V4=0.77 volts TMP4=27.15 degrees C F4=80.87 degrees F
S5:V5=0.77 volts TMP5=26.66 degrees C F5=79.99 degrees F

S1:V1=0.77 volts TMP1=27.15 degrees C F1=80.87 degrees F
S2:V2=0.78 volts TMP2=27.64 degrees C F2=81.75 degrees F
S3:V3=0.77 volts TMP3=26.66 degrees C F3=79.99 degrees F
S4:V4=0.77 volts TMP4=27.15 degrees C F4=80.87 degrees F
S5:V5=0.77 volts TMP5=27.15 degrees C F5=80.87 degrees F

S1:V1=0.77 volts TMP1=27.15 degrees C F1=80.87 degrees F
S2:V2=0.77 volts TMP2=27.15 degrees C F2=80.87 degrees F
S3:V3=0.76 volts TMP3=26.17 degrees C F3=79.11 degrees F
```

Fig. 5 Data under normal condition

C. System Performance Monitoring

Operational data showed battery temperatures averaging 32.0–32.8°C, humidity between 52–55%, and motor speed constant at 62%. The buzzer remained OFF, confirming that threshold safety logic was not triggered. Regression analysis revealed predictive consistency: temperature regression flagged elevated values (>32°C), humidity regression achieved high accuracy ($R^2 \approx 0.98$), and motor speed/battery regression models supported proactive control. These predictive insights ensure the system can anticipate unsafe conditions before they occur. System monitoring in real time is show in Fig 6,7,8.

D. Comparative Discussion

Hardware validation confirmed PCM's role in stabilizing battery temperatures, while predictive modelling extended the evaluation to long-term scenarios. which relied solely on hardware data, this integrated approach combines real-time monitoring with predictive forecasting, enabling proactive safety management. The dual methodology ensures both immediate reliability and forward-looking resilience.

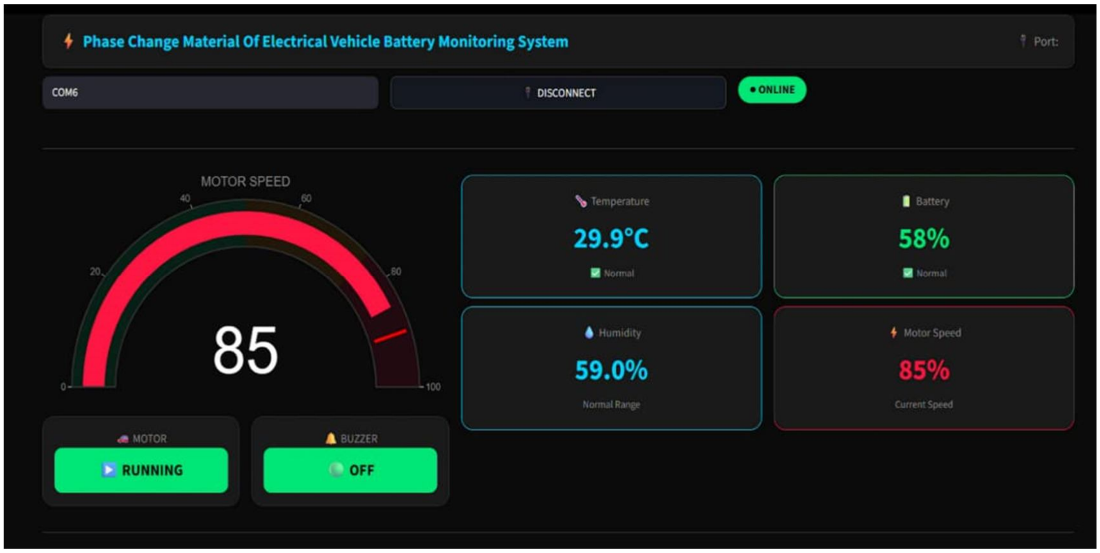

Fig. 6 Software dashboard

Fig. 7 Real time data monitoring

Fig. 8 Predictive analysis with respective time

E. Implications

The results demonstrate that PCM combined with predictive monitoring provides a scalable framework for EV battery cooling. This integration ensures real-time safety and anticipatory control, making it suitable for next-generation EV applications where efficiency, reliability, and safety are critical.

V. CONCLUSION

This study presented a dual methodology integrating hardware experimentation with predictive modelling for electric-vehicle battery thermal management. The experimental results confirmed that Phase Change Material (PCM) effectively stabilized battery temperatures, maintaining values within safe operating limits and reducing the risk of localized hotspots. Predictive analysis further demonstrated PCM's capacity to absorb approximately 18 kJ of heat during phase transition, with a liquid fraction of 0.6 at 41°C, validating its buffering ability under dynamic load conditions.

The integration of real-time sensor monitoring with predictive forecasting provided a proactive framework for safety management. Unlike hardware-only approaches, this system anticipates critical temperature rise and activates control mechanisms before thresholds are exceeded. Regression analysis of operational parameters strengthened the predictive capability, ensuring reliable monitoring of temperature, humidity, motor speed, and battery performance.

Overall, the results highlight that PCM combined with predictive monitoring offers a scalable, reliable, and forward-looking solution for next-generation EV battery cooling. This approach not only enhances safety and efficiency but also establishes a foundation for intelligent thermal management systems capable of adapting to diverse operating conditions.

VI. ACKNOWLEDGMENT

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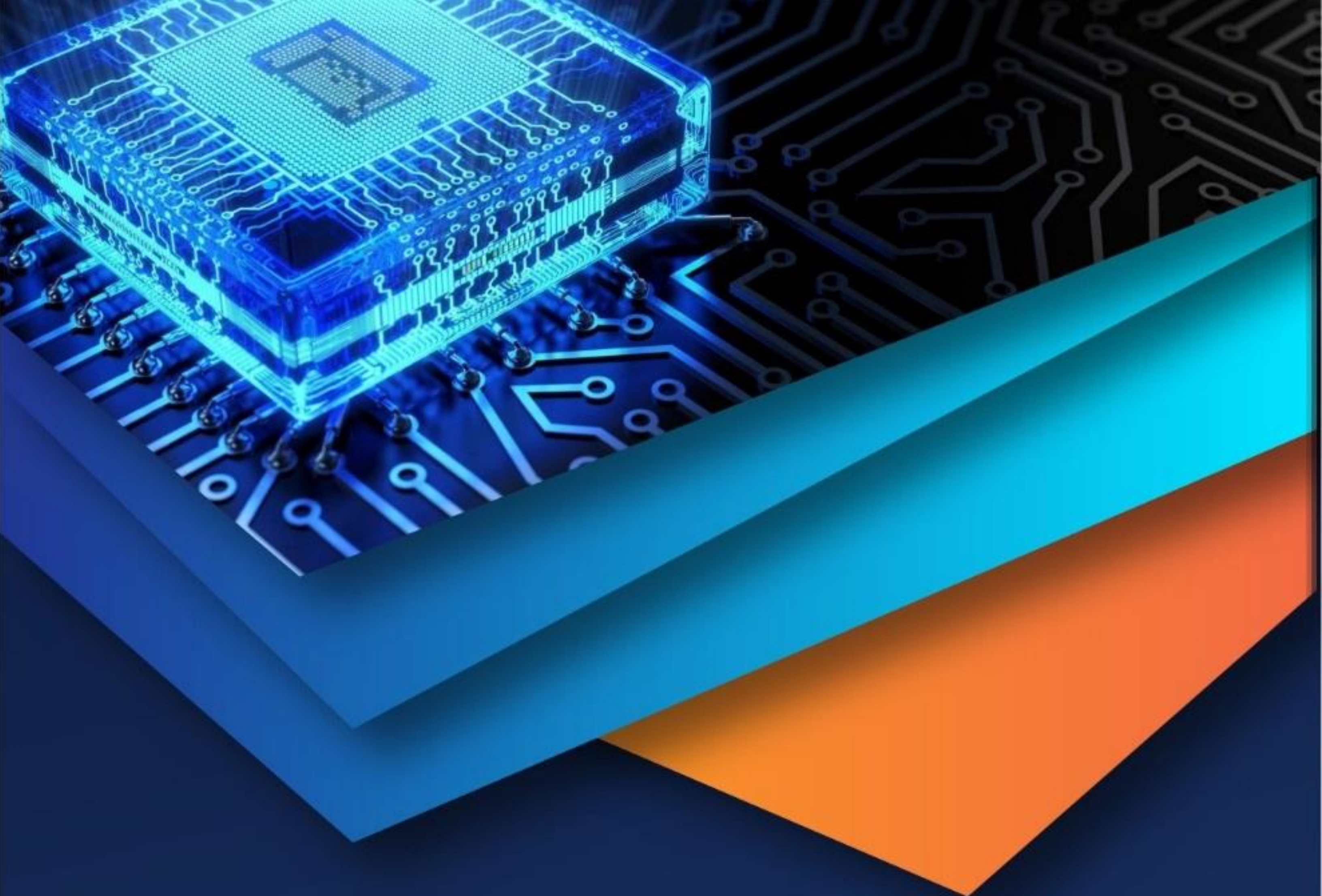

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