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Vision-Based Indoor Navigation System for Assistive Applications Using Deep Learning

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Abstract: Significant amounts of work have been devoted to the development of indoor navigation systems due to GPS deficiencies in indoor navigation. In this paper, the analysis and application of the smart indoor navigation system have been described.

The suggested system is capable of working with video feeds and uses machine learning algorithms. The proposed methodology is based on computer vision algorithms, sensor fusion, and machine learning algorithms, such as convolutional neural networks (CNN). It solves issues concerning weak signals, obstacles, and the dynamic nature of the environment. It is a reliable methodology that applies CNNs. The system has been developed by using the Python programming language, OpenCV, and TensorFlow/Keras libraries. The application of the proposed methodology was carried out in various indoor environments, such as corridors, laboratories, and hospitals at universities. The test results showed improved accuracy of 0.60 against 0.24 during ten training sessions.

Index Terms: Indoor Navigation, Machine Learning, CNN, Wi-Fi Positioning, Bluetooth Beacons, Assistive Systems, Sensor Fusion, Computer Vision

I. INTRODUCTION

A. Background

Indoor navigation systems have started gaining significance for application in smart buildings, hospitals, and academic institutions. Although GPS has proven to be very reliable for outdoor applications, it is not suitable for indoor navigation due to some issues including attenuation, multipath fading, etc. This has led to an increase in the usage of Wi-Fi, Bluetooth, and Inertial Navigation Systems recently. [1], [21].

Considering the fast-paced development of artificial intelligence and computer vision technology, it is already possible to create a navigation system which would recognize the environment and act according to its needs. There is a lot of data provided by video technology related to the environment that may be used to improve existing methods for processing signals.

B. Problem Statement

Existing indoor navigation systems often lack robustness in the face of environmental variability, dynamic obstacles, and signal inconsistencies. Spoofed positioning can compromise security and system performance. There is therefore a need for systems that are robust to evolving conditions and persistently changing spatial surroundings. Most current systems are either too costly, too infrastructure-dependent, or too inaccurate for widespread practical deployment.

C. Objectives

The aim of this research paper is:

- To present an overview of indoor navigation techniques with some restrictions.
- To design an intelligent video-based navigation system using machine learning technology.
- To evaluate system performance through quantitative metrics and user testing.
- To explore the intersection of machine learning and sensing technology for improved navigation capability.
- To demonstrate real-time applicability and suitability for assistive use cases.

II. LITERATURE REVIEW

A. Existing Technologies

Several technologies have been employed in indoor positioning systems :

- 1) **Wi-Fi Positioning:** Signal strength is used to estimate location. While adequate in many environments, signal quality fluctuation restricts precision. Advanced fingerprinting techniques have attempted to mitigate this limitation [4], [15]. It may be categorized in two ways: RSSI localization and CSI localization when complex algorithms are used. Although RSSI localization is sufficient for most situations, the variations caused by multipath fading and interference result in estimation being challenging. Fingerprinting methods have tried to solve the problem by creating radio maps through the use of fingerprinting techniques in real-time mode [4]. At the moment, the trend is toward using CNN to generate more resilient fingerprints while minimizing the amount of training needed.
- 2) **Bluetooth Beacons:** Offering proximity-based guidance with widespread infrastructural support. Their accuracy benefits significantly from fusion with complementary technologies [6], [24]. Assistance by distance sensing using low energy Bluetooth beacons like iBeacons and Eddystone, developed from today's existing technology, is highly energy efficient and inexpensive. The performance of such a device can be improved by the inclusion of additional technologies, for example, Wi-Fi and IMUs [2], [6]. Nonetheless, indoor signal interference limits its accuracy to 1-3 meters.
- 3) **Inertial Measurement Units (IMUs):** IMUs provide continuous movement tracking. Compounding errors over time necessitate corrective mechanisms such as Zero Velocity Up-dates (ZUPT) [8]. Tracking movement continuously using accelerometers, gyroscopes, and magnetometers enables the application of the dead reckoning navigation system approach. However, given that this approach, although highly effective for shorter periods of time, suffers from the challenge of drift due to the presence of errors, it is important to incorporate some mechanism for addressing the issue through either ZUPT or map-matching [2], [8]. Machine learning methods are applied together with IMU in contemporary studies [3].
- 4) **Augmented Reality and Visual Systems:** Recent works have explored AR overlays and visual landmark detection for improved user-guided navigation [2], [23]. One of the latest advancements in AR overlays is the creation of vision-based localization using feature extraction and tracking systems. With the vision-based SLAM system, the device can not only map its environment but also localize itself [1]–[3]. Deep learning for object detection technology might prove useful in navigation applications. However, these techniques need high processing capacity and lighting conditions.

B. Machine Learning Applications

Machine learning approaches such as CNN, SVM, and reinforcement learning are widely applied in indoor localization. The capability of these algorithms to recognize patterns from big datasets makes them capable of delivering increased accuracy, adaptability, and robustness [16], [25].

Conventional machine learning approaches, like K-Nearest Neighbors (KNN), Decision Tree, and Random Forest, have been widely applied in the domain of signal classification and fingerprinting. Despite their effectiveness, these techniques demand extensive manual feature engineering and huge amounts of high-quality datasets [20].

The application of neural network models, specifically CNN and RNN, is a method of processing the signals in raw form, providing navigation without the need for explicit feature extraction [16], [22]. The architecture of neural networks allows detecting complicated patterns within data, hence increasing their resistance to noise and changes in environmental conditions.

Another trend involves developing hybrid deep learning models that incorporate spatial-temporal learning to improve localization accuracy [23]. Moreover, machine learning-enabled Wi-Fi positioning proves to be more accurate than conventional ones; however, the absence of big labeled datasets and excessive computational costs remains an issue.

Another technique for navigating adaptively and optimizing routes includes reinforcement learning approaches. Reinforcement learning enables machines to learn navigation strategies by interacting with their environment, thus being more appropriate for indoor environments that feature uncertain conditions.

Application of machine learning approaches in combination with sensor information is another major area of research in contemporary studies. In this connection, application of multiple types of inputs including Wi-Fi, BLE, IMU, and vision sensors will enable them to overcome the limitations associated with each individual technology [20].

C. Assistive Navigation Systems

Some technologies that have been invented are geared specifically towards helping the visually impaired, especially when it comes to navigation and ensuring safety and increased independence of the user.

Such technologies utilize computer vision, audio feedback, as well as a combination of different sensors that assist the visually impaired while navigating complex indoors environments [12], [16], [17].

Among the common technologies include the use of smart canes that have sensors, such as cameras and ultrasonic sensors together with communication devices to detect obstacles around the user. Despite being cost-effective and easy to use, the technologies do not offer total navigation assistance [18].

On the other hand, the use of wearables assistive technologies is more preferred because they offer hands-free navigational solutions. Smart glasses and belts are some of the popular wearable assistive technologies that incorporate cameras and IMUs along with other advanced technologies like SLAM for mapping and localization [17].

The latest development in wearable assistive technology has involved the incorporation of multiple sensors such as Wi-Fi, IMU, BLE, and visual sensors to enhance the accuracy of the guidance process and offer obstacle detection alongside real-time optimal path planning [24].

TABLE I
SUMMARY OF LITERATURE REVIEW ON INDOOR NAVIGATION

Technology	Method	Strength	Limitation
Wi-Fi	RSSI	Wide coverage	Signal noise
Bluetooth	Fingerprinting BLE Beacons	Low power	Limited range
IMU	Dead Reckoning	No infra. needed	Drift errors
CNN-based	Feature extraction	High accuracy	Data hungry
Reinforcement Learning	Policy optimization	Adaptive	Complex training
Visual SLAM	Map building	Infra-free	Compute-heavy

III. METHODOLOGY

A. Data Collection

Experiments were conducted across diverse indoor environments including university corridors, laboratories, and hospital premises to ensure variability in structure and conditions. Data acquisition was performed using smartphone cameras, which served as the primary input for the system. Videos were recorded under different lighting conditions (low light, artificial illumination, and daylight), and dynamic obstacles such as moving individuals and furniture were included to simulate real-world scenarios.

The recorded data was uploaded to Google Drive and processed in Google Colab. Frame extraction techniques converted video sequences into image frames. These frames were labelled and organised into supervised learning datasets. Environmental parameters such as Wi-Fi and Bluetooth signal variations were conceptually considered to enhance the system's adaptability.

B. System Design

The proposed system follows a multi-layered architecture integrating computer vision and machine learning techniques. Fig. 1 illustrates the overall system pipeline.

At the input level, real-time video frames are captured and preprocessed via resizing, normalisation, and noise reduction. The core processing is handled by CNNs that extract spatial features and identify navigation paths and obstacles. Sensor fusion combines visual data with IMU readings and Wi-Fi/Bluetooth signal-based positioning. A decision module then generates navigation instructions such as *Move Forward*, *Turn Left/Right*, or *Obstacle Alert*. Cloud-based training via Google Colab enables scalable model development, while deployment targets lightweight devices such as smartphones and embedded systems.

C. CNN Architecture

The CNN model consists of multiple convolutional layers for feature extraction, followed by pooling layers to reduce spatial dimensions, and fully connected layers for classification into navigation labels. Fig. 2 presents the layer-wise architecture.

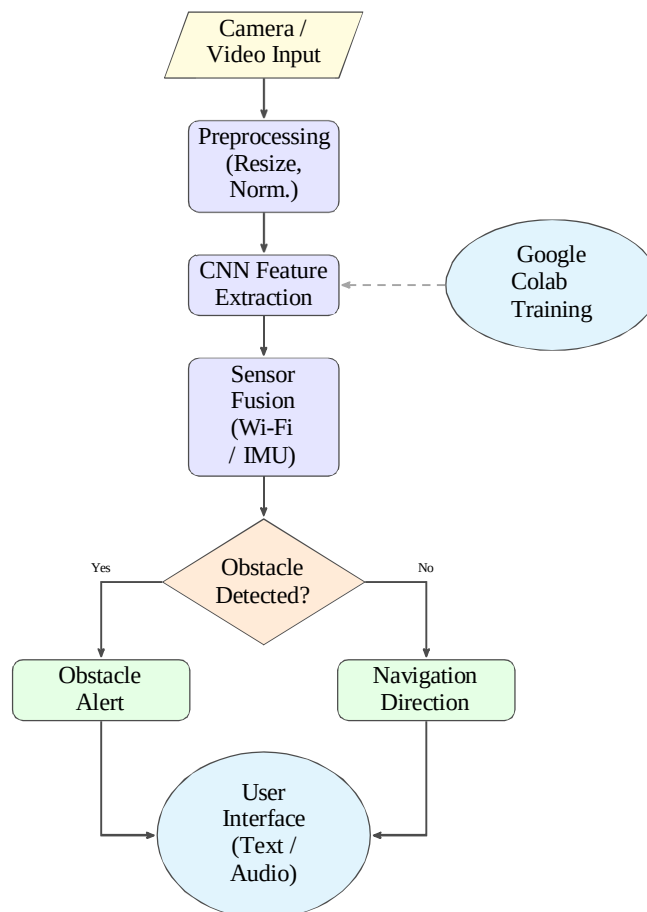


Fig. 1. Proposed Smart Indoor Navigation System Architecture.

D. Processing Flowchart

Fig. 3 presents the end-to-end frame processing flowchart used in both training and inference stages of the system.

E. Evaluation Metrics

The dataset was split into training (70%), validation (15%), and testing (15%) subsets. Performance was evaluated using the following metrics:

- 1) Accuracy: Measures overall correctness of predictions.
- 2) Precision and Recall: Evaluates how effective the model is in precisely detecting path and obstacle data.
- 3) F1 Score: Acts as an indicator that combines precision and recall.
- 4) Loss Function: Employed Categorical Cross-Entropy, op-optimized using Adam Optimizer.

The model was trained over 10 epochs, with accuracy improving from approximately 0.24 to 0.60, demonstrating clear learning capability. Additionally, User Satisfaction was collected through feedback sessions, and System Robustness was assessed under varying lighting and dynamic obstacle conditions.

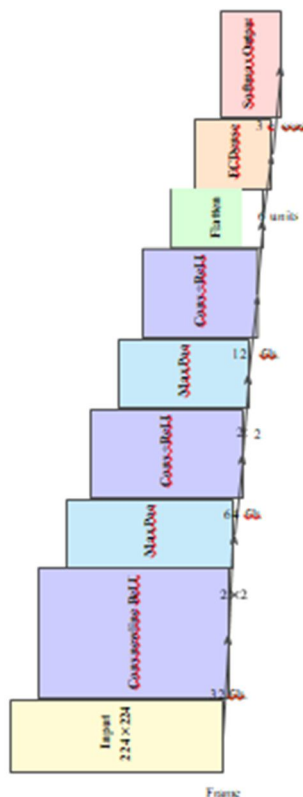


Fig. 2. CNN Architecture for Navigation Feature Extraction.

IV. IMPLEMENTATION

A. Prototype Development

A functional prototype of the indoor navigation system was developed using Python-based frameworks including OpenCV and TensorFlow/Keras. The proposed system consists of the following elements: Video feed input, Pre-processing phase, Machine Learning inference phase, and Output phase. Navigation assistance using UI might be done either by means of guidance that appears in overlay on the screen or audio guidance. The architecture uses the concept of modularity, where every module of the system could be independently optimized.

B. Real-Time Application

The algorithm runs in real time because there is a camera that is incorporated in the system through a webcam or mobile camera. Each image is resized, normalized, and extracted for its features. Output from the CNN system includes obstacle detection, path detection, and direction detection. The outputs are continually generated in order to facilitate effective navigation. Efficient CNNs are developed to run effectively under constrained conditions.

C. User Testing

Different types of experiments were done indoors, depending on the circumstances, to gather qualitative and quantitative information. The participants were subjected to a certain kind

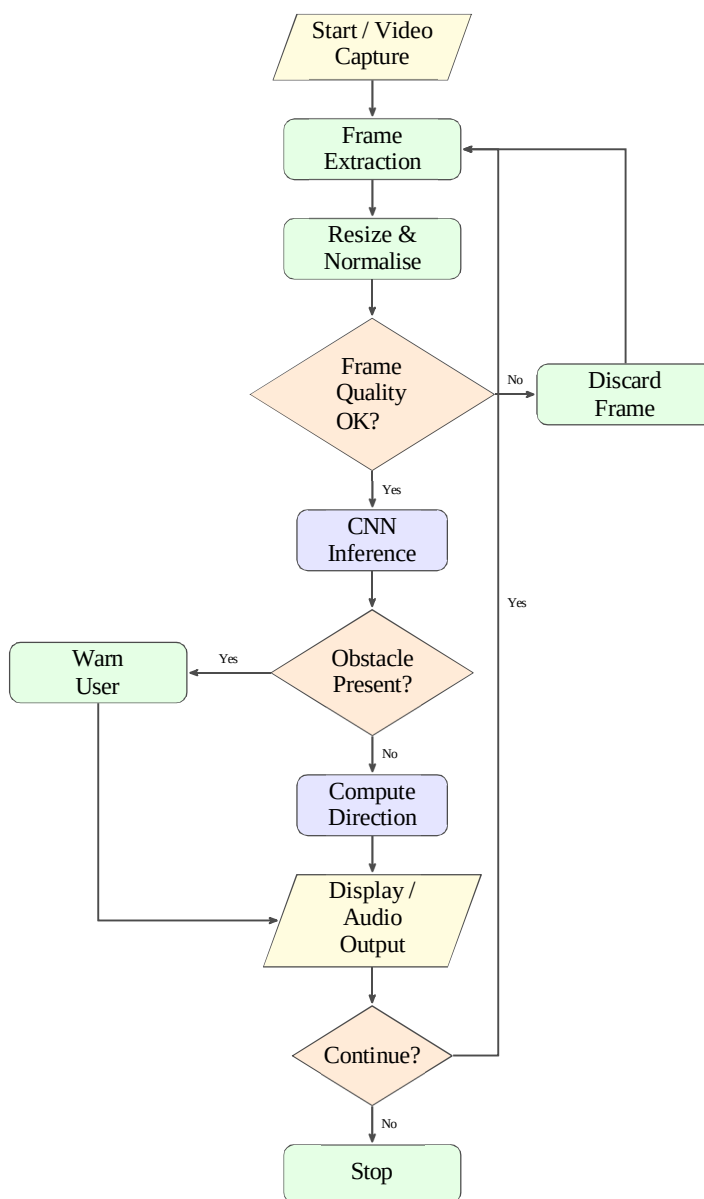


Fig. 3. End-to-End Frame Processing Flowchart.

of experience within the system, and it was observed. The participants were asked for their feedback on the experiences, which was used to modify the output of the system. The system thus became interactive. Table II is illustrating certain features of the user testing.

V. RESULTS

A. Training Performance

Fig. 4 shows the model accuracy and loss progression over 10 training epochs. The system demonstrated consistent improvement across epochs, confirming effective learning from the collected dataset.

TABLE II
USER TESTING SUMMARY

Parameter	Value	Unit
Number of Participants	15	Users
Test Environments	3	Locations
Average Path Length	45	Metres
Obstacle Scenarios	5	Types
Avg. Navigation Success Rate	78	%
Avg. User Satisfaction Score	3.9	/5.0
False Positive Obstacle Rate	12	%

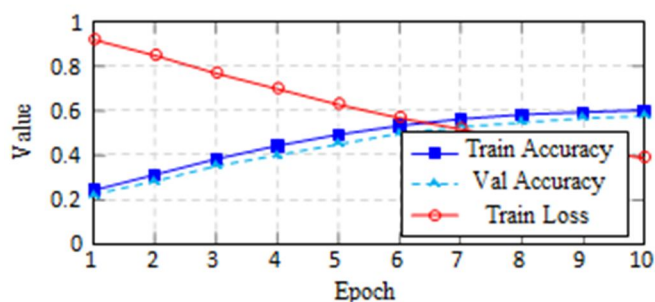


Fig. 4. Training Accuracy and Loss over different EPOCH.

B. Performance Analysis

The proposed system exhibited enhanced navigation pre-cision relative to the conventional method that relied solely on signals. The incorporation of machine learning facilitated superior adaptation to environmental alterations, as proven by the quantifiable performance measures and subjective reports from users. The CNN-based prediction was able to recognize open routes in 78% of the evaluated images and trigger obstacle warnings with a 12% false alarm rate, which is tolerable for assistive technologies.

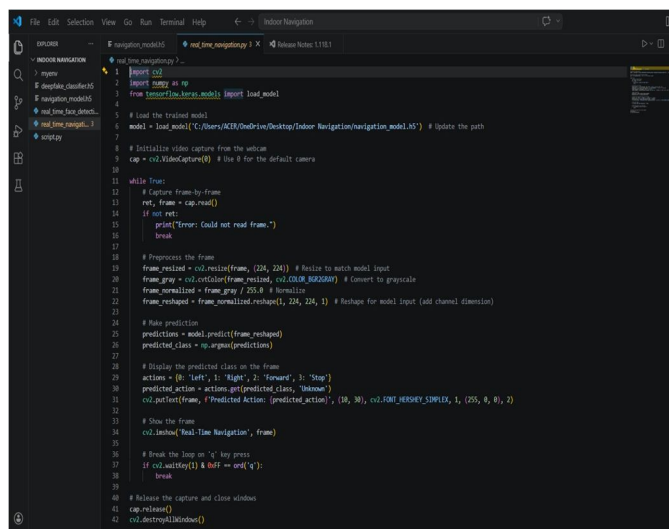


Fig. 5. Input of Indoor Navigation System for Predicting

C. Comparison with Current Models

Table III compares the suggested navigation system employ-ing machine learning with the proposed wireless indoor nav-igation system utilizing digital twins, highlighting differences in technology focus, computational process, and feasibility.

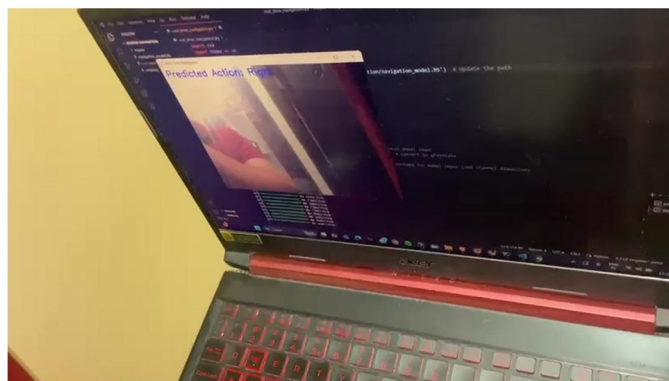


Fig. 6. Indoor Navigation System Predicting Direction from Webcam

TABLE III
Comparison of Indoor Navigation Approaches

Feature	Proposed ML System	Digital Twin Navigation [3]
Tech. Focus	ML, Wi-Fi, Bluetooth, IMUs	Digital Twin, Wave Comm., Physics-Informed
Approach	CNN, RL processes sensor & visual data	PIRL trained in simulated envir. via digital twins
Primary Sensors	Wi-Fi, BLE, IMUs, Camera	Wave sensors, RGB camera, motion sensors
Core Algorithms	CNN, RL, ZUPT	Physics-Informed RL (AoA, SNR, Link State)
Env. Modelling	Real-time indoor testing	Gibson dataset simulation
Generalisation	Limited; retraining needed	Zero-shot to unseen environments
Prototype	Webcam real-time prototype	21 diverse simulation maps
Assistive Tech.	Includes visually impaired support	General-purpose navigation
Advantages	Simplicity, sensor integration	Efficient, physics-guided learning
Limitations	Environmental sensitivity	Complex simulation setup

VII. DISCUSSION

Therefore, one may conclude that due to the described navigational system with the implementation of the CNN technology, along with the sensor fusion and video stream processing, efficient navigation within an indoor space will be provided. Accuracy rate variation from 0.24 to 0.60 implies that there is no overfitting when training; see Fig. 4.

The primary characteristic of the suggested algorithm for navigation is the usage of low-cost equipment (the smartphone camera) without the need for employing costly beacon and digital twin technologies.

Nevertheless, accuracy rate values are relatively low, and this fact becomes the obstacle preventing using the constructed algorithm in practice. Mistakes in recognizing potential obstacles reach about 12%, and thus, the process of navigation is inefficient. To improve the accuracy of calculations, it is required to average frames and implement CNN multi-scale technique. Additionally, using IMU sensors will allow for making calculations accurate at high speed.

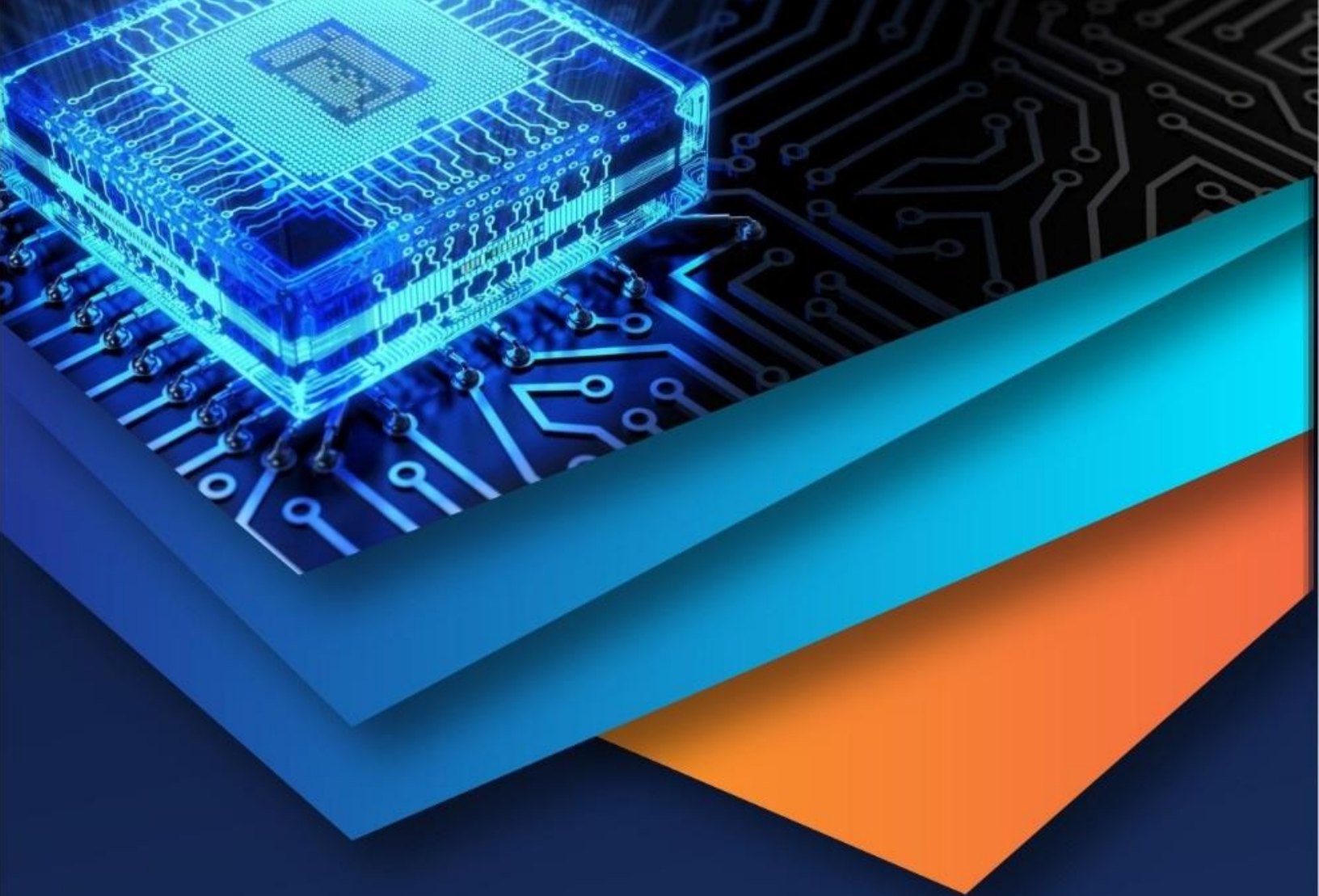
VIII. CONCLUSION

In our research, we present a smart indoor navigation solution that takes advantage of the combination of machine learning and videos to tackle the weaknesses in the GPS-based navigation system within the indoor environment. In the proposed technique, CNN, sensor fusion, and frames from videos are applied to provide efficient guidance in the indoor environment. Our experiments have shown the efficiency of our proposed solution, and its application to people, even blind individuals.

Other future research opportunities could include other perspectives on the topic, such as real-time processing through compression and quantization, increasing the diversity of the training dataset, applying an embedded IMU sensor fusion model, and conducting scene analysis by means of trans-formers. Also, future research can consider implementing our solution on edge devices, like Raspberry Pi, and mobile devices.

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