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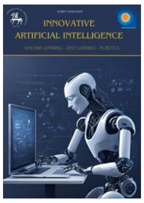

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RESEARCH ARTICLE

Integrated Smart Waste Management System Based on Artificial Intelligence and IoT

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Abstract

This study presents an innovative smart waste management system developed through the integrated use of artificial intelligence, IoT (Internet of Things) and mobile technologies. The system features a multi-layered architecture that combines sensor-based data collection, real-time monitoring via a cloud infrastructure, AI(Artificial Intelligence)-assisted waste classification and user interaction. Container occupancy rates were measured using an ESP32 microcontroller and ultrasonic sensors, and the data was transferred to the Firebase infrastructure. In the image classification process, the CNN model achieved 94.5% accuracy, while the Gemini model, which requires no additional training, demonstrated superior performance with 97.1% accuracy. The mobile application increased users' recycling awareness, while the web-based panel provided occupancy tracking and route optimization for managers. The results demonstrate that the hybrid CNN-Gemini approach increases waste classification accuracy and system efficiency. This holistic structure is considered a low-cost, scalable and environmentally friendly solution for sustainable smart city applications.

Keywords: *Artificial intelligence, Deep learning, IoT sensor, Smart Waste Management, Sustainability*

1. Introduction

The rapidly increasing global population, urbanization rates and changing consumption habits have become an environmental problem that exceeds the capacity of existing waste management systems. Although a global decline in fertility rates is observed, the total population continues to grow. Dawson et al. [1] emphasized in their study that the world population will exceed 8 billion by 2024. This increase is not only a demographic phenomenon but also an environmental indicator directly reflected in the amount of waste. Indeed, during the same period, daily waste production per capita increased from 0.4 kg to 0.7 kg [2]. As seen in Figure 1, there is a clear direct correlation between global population and per capita waste production.

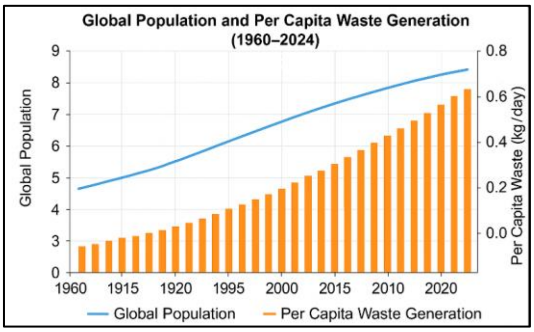

Figure 1. World population and daily waste production per capita (1960–2024). Data from [1] and [2].

With the acceleration of urbanization, the increasing consumption of ready-made foods, especially in large cities, has significantly increased the volume and variety of packaging waste. Local governments are struggling to manage this increased waste with existing infrastructure, leading to increased collection and transportation costs [3, 4]. As part of the Zero Waste Campaign conducted by the Ministry of Environment, Urbanization and Climate Change, the recycling rate of packaging waste across Türkiye has increased from 13% in 2017 to 36.08% by 2025 [5]. Such examples demonstrate the impact of awareness-raising and data-based management.

Incorrect or incomplete waste separation exacerbates not only environmental impacts but also economic losses. Mixing recyclable materials with organic or hazardous waste not only harms nature but also disrupts reuse processes, leading to wasteful use of resources [2, 6-7]. This threatens sustainable development goals and places an additional burden on public budgets [8].

Recent studies in the literature clearly demonstrate the direct relationship between socioeconomic indicators and environmental performance. According to data from the UNDP (United Nations Development Programme)'s Human Development Data Center, Türkiye's Human Development Index (HDI) rose from 0.598 in 1990 to 0.855 in 2022 [9]. During the same period, data from the

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European Environment Agency (EEA) show that the municipal waste recycling rate increased from 1% in 2010 to 12% in 2022 [10]. The simultaneous increase in these two trends reveals the relationship between environmental sustainability and economic and social development. Figure 2 shows the rise in the HDI and the recycling rate in Türkiye, highlighting the parallel development of environmental awareness and welfare indicators.

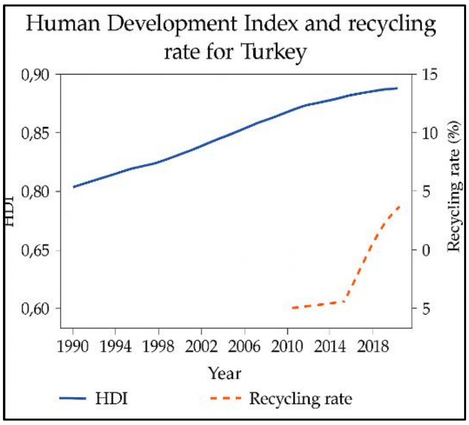

Figure 2. HDI and municipal waste recycling rate in Türkiye (1990–2022). Data from: [9] and [10].

In traditional waste management, collection activities conducted on fixed routes without considering the occupancy of containers result in both time and fuel loss. Collection and transportation costs, the highest cost item in solid waste management, can reach up to 80% of the total cost [3]. IoT-based sensors and dynamic route optimization offer a significant solution in this regard; literature reports reductions of 25–30% in fuel consumption, 20–25% in transportation distances, and 10–12% in operating costs [11, 12].

In recent years, artificial intelligence and deep learning-based image classification methods have attracted attention with their high accuracy rates in waste separation processes. Convolutional Neural Network (CNN) architectures demonstrate effective performance in distinguishing different waste types, and multimodal AI approaches (e.g., Gemini) further strengthen this process [13-17]. This reduces the need for manual operations and indirectly reduces carbon emissions.

In this study, we combined approaches discussed in parts of the literature and developed an integrated smart waste management system. The system is designed to increase individuals' awareness of recycling, provide real-time data to municipalities and optimize collection processes. In the application layer, users are educated through educational content and motivated through a gamification-based reward system via a Flutter–Firebase-based mobile platform. In the field layer, container fill rates are measured using an ESP32 microcontroller and ultrasonic sensors, and this data is transmitted to the cloud infrastructure. At the same time, an AI classification component working with CNN and Gemini models automatically categorizes waste. The web panel on the administrator side analyzes this data to enable dynamic route planning and performance monitoring. The overall system architecture is presented in Figure 3. This diagram illustrates the data flow between the user, IoT sensors, cloud infrastructure and AI components, visually demonstrating the system's scalable and modular structure. This article consists of five sections and the organization is as follows: Section Two explains dataset, data preparation, mobile application development tools, AI tools for waste separation and IoT sensor used in this study. Section Three tells the results and performances of the models. Section Four provides discussion over the results and Section Five concludes the article.

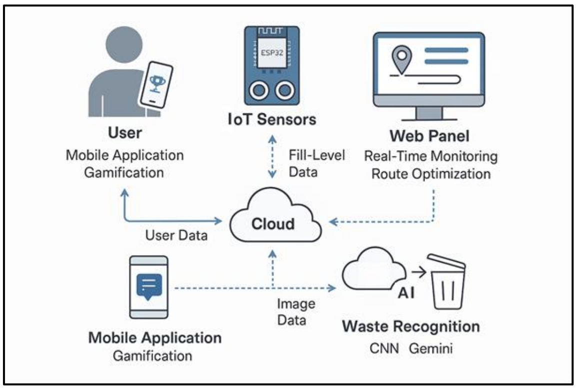

Figure 3. The overall architecture of the smart waste management system.

2. Materials and Methods

This study covers the design of a multi-layered system consisting of a mobile application, an IoT-based sensor network, AI-based image classification and a web-based management panel. The general technical infrastructure of the developed system is presented in Figure 4. This structure illustrates the interaction between the user (mobile device), cloud infrastructure (Firebase), AI classification unit (CNN + Gemini), sensor module (ESP32 + ultrasonic sensor) and management panel (web server) components.

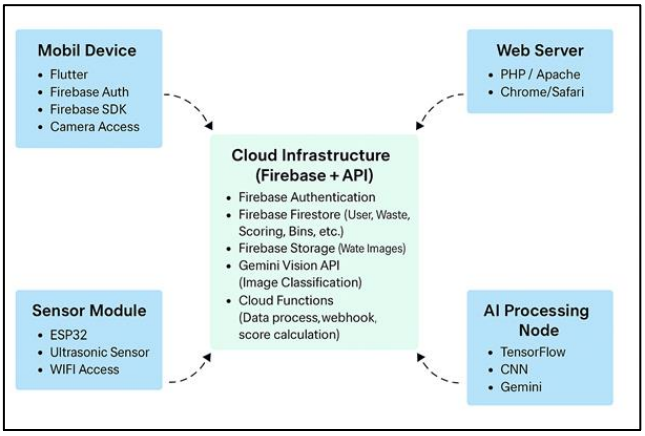

Figure 4. Overall system architecture of the proposed smart waste management framework integrating IoT sensors, AI classification, cloud infrastructure and mobile/web interfaces.

2.1. Dataset

In this study, a CNN-based model was developed to automatically classify solid waste. The dataset used is the *TrashNet* dataset, published on the *Kaggle* platform [18]. The dataset, which contains a total of 2527 images, includes the categories "cardboard, paper, glass, plastic, metal and garbage." However, in this study, the classes "garbage" and "cardboard" were excluded due to insufficient sample numbers and the imbalance in the data. Following this process, the dataset was reorganized into four main classes (paper, glass, plastic and metal). The final dataset contains a total of 1987 images and the proportional distribution of the classes is shown in Figure 5.

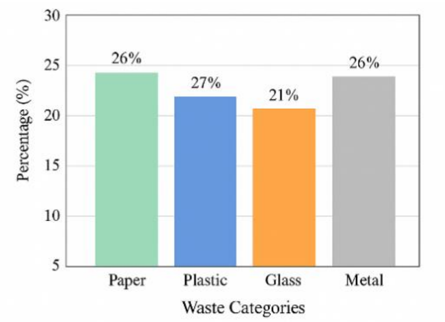

Figure 5. Distribution of waste categories in the dataset (Paper, Plastic, Glass, Metal).

Each image in the dataset was captured at a resolution of 512x384 pixels, on a white background and under various lighting conditions. In the pre-processing phase, the images were rescaled to 224x224 pixels, class labels were converted to numerical values and pixel values were normalized. Data augmentation operations such as rotation, shift, brightness adjustment and mirroring were applied to improve the model's generalization ability.

2.2. Mobile Platform

The Flutter framework and Firebase services were used together in the mobile application development process [19, 20]. *Flutter* offers a high-performance user interface that runs on both Android and iOS operating systems with a single codebase. *Firebase Authentication* was used for user authentication, *Cloud Firestore* for storing user data and *Firebase Storage* for storing waste photos. The integration of these services ensures the system has a robust structure in terms of data security, scalability and speed.

The developed application allows users to view nearby waste bins on a map, receive directions to the nearest location and track their recycling contributions through a scoring/badge system. Figure 6 shows the user interface representation of these features.

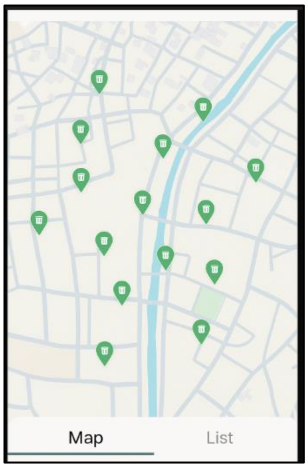

Figure 6. Mobile application interface displaying nearby smart bins in the city center

2.3. Automatic Waste Separation

The CNN architecture was used in the automatic classification of waste and a comparative analysis was conducted with the Gemini model, a modern artificial intelligence tool [14-17, 21]. The CNN architecture demonstrates particularly high success in extracting features from image data in a hierarchical manner. Additionally, each image in the dataset was sent to the AI via the *Gemini Vision API* [22] to obtain class predictions. Thus, the system moved beyond a solution based solely on a local CNN model to a hybrid classification system integrated with cloud-based AI services.

2.4. Web Panel

The web panel was developed to allow administrators to monitor system performance, view occupancy rates, and make route optimization decisions. HTML-CSS, JavaScript, and PHP technologies were used in the panel's creation. This structure allows administrators to:

- Monitor the occupancy status of each waste bin,
- Live occupancy rate data,
- Erroneous sensor measurements and fault records in real time.

This panel provides the ability to monitor and intervene in the overall operation of the system, making it a scalable control interface for smart city management systems.

2.5. IoT Sensor

The sensor component of the system (Figure 7) consists of the *ESP32* microcontroller, ultrasonic sensor, antenna and power unit modules [23–27]. Ultrasonic sensors measure the fill rate of garbage containers and the obtained data is transferred wirelessly to the *Firebase Realtime Database* via ESP32.

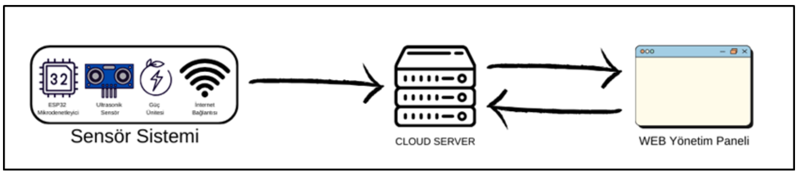

Figure 7. Hardware configuration of the IoT-based sensing unit using ESP32 microcontroller, ultrasonic sensors, antenna, and power supply unit.

ESP32 was an ideal microcontroller for this study thanks to its low power consumption and integrated Wi-Fi module. The prevalence of similar ESP32-based applications in the literature supports the device's reliability in such smart city solutions [28, 29]. The power supply unit ensures the ESP32's safe operation by reducing the 220V mains voltage to 3.6V. The antenna module is used to improve data transmission quality in areas with low signal reception. These hardware components contribute to the stable operation of the system under field conditions.

3. Results

The model's performance was evaluated using two different artificial intelligence approaches: a locally trained CNN model and a closed-source Gemini multimodal model developed by *Google DeepMind*. The CNN model was trained for 25 epochs using a classical training-validation-testing split, and epoch-based accuracy and loss curves were obtained. As seen in Figures 8 and 9, the model's accuracy showed a steady increase throughout the training process. The initial accuracy, which was 72%, rose to 94% with increasing epoch numbers. The loss curve decreased from 0.63 to 0.14 during the same period and exhibited a stable trend in the final epochs. This demonstrates that the model generalizes stably without overfitting.

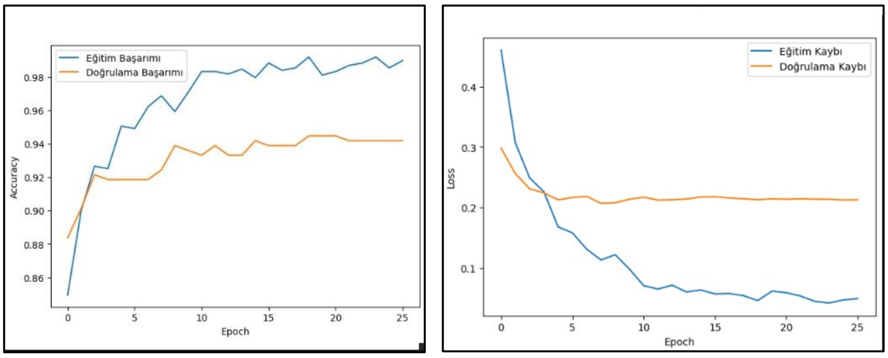

Figure 8 -9. Training accuracy(left) and loss curve (right) of the CNN model across 25 epochs.

After training was completed, the model was tested separately for four waste categories (paper, plastic, glass and metal). The resulting class-based performance metrics are presented in Table 1. According to the results, the highest performance was observed for the plastic category, while the lowest was observed for the glass category. The average classification accuracy was calculated as 94%. These results demonstrate that the model performed balanced learning on the dataset and has a low-variance error profile.

Table 1. Performance metrics of the CNN model for four waste categories.

	Precision	Recall	F1-score	Support
Glass	0.96	0.90	0.93	86
Metal	0.91	0.95	0.93	86
Paper	0.97	0.97	0.97	86
Plastic	0.94	0.97	0.95	86

The complexity matrix of the CNN model is shown in Figure 10. The high density along the diagonal indicates a predominance of correct classifications, while the partial confusion between glass and metal classes can be explained by light reflections in the images. Since the high-gloss surfaces of metal waste exhibit similar optical properties to glass waste, a significant portion of the classification errors was concentrated in these two classes. Furthermore, the model demonstrated high consistency in visually distinct classes such as paper and plastic.

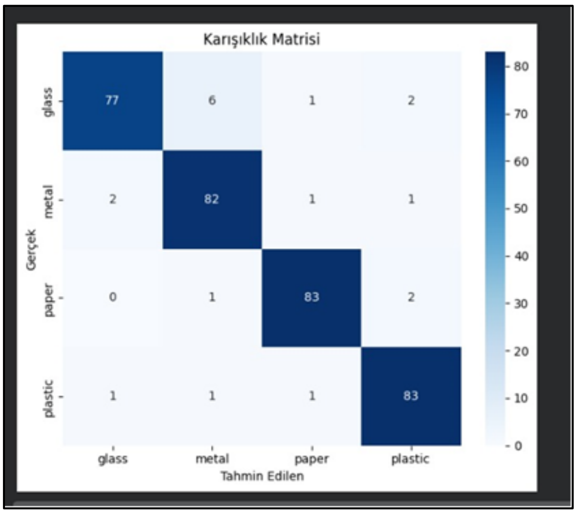

Figure 10. Confusion matrix of the CNN model on the test dataset.

In the evaluation of the Gemini model, due to the closed-source nature of the system, classical training or batch testing could not be applied. Instead, each test image in the dataset was loaded into the model individually and the model's prediction outputs were labeled as "correct" or "incorrect." A manual accuracy analysis resulting from this process revealed Gemini's overall performance. Similar studies exist in the literature on user-level testing of closed-source multimodal models [21, 30] and this method is widely used, especially in API-based access. Figure 11 shows the resulting complexity matrix. The partial error rate in the glass class was due to optical reflections and the model's tendency to match similar surface textures during generalization.

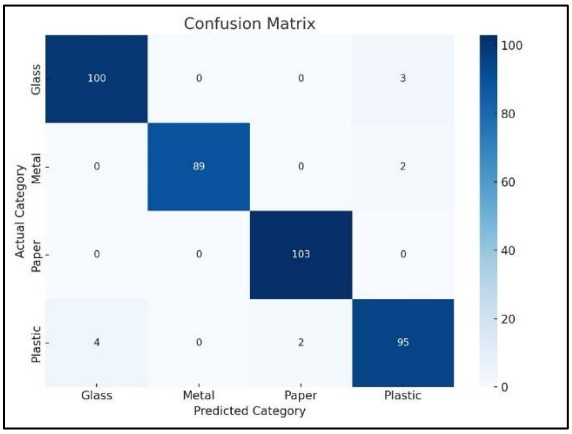

Figure 11. Confusion matrix of the Gemini model showing class-level prediction performance.

Figure 12 graphically summarizes the Gemini model's class-based precision, recall, and F1 values. Success rates exceed 90% across all classes, with a 98% success rate particularly in the plastic and paper categories. These results are consistent with the generalization capabilities of multimodal AI systems reported by Radford et al. [31].

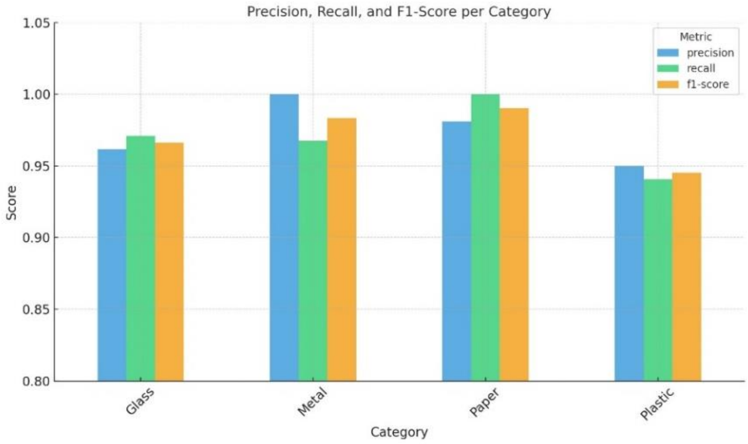

Figure 12. Comparison of Gemini model evaluation metrics across four classes.

In the comparative analysis, the accuracy, precision, recall and F1-score values of both models were examined together. The CNN model demonstrated high stability with an average accuracy of 94.5%, while the Gemini model demonstrated 2.6% higher overall performance with an average accuracy of 97.1%. The Gemini model also provided approximately a 1–2% improvement over the CNN in terms of precision and F1 values. Table 2 provides a side-by-side comparison of the key metrics of both models.

Table 2. Comparison of CNN and Gemini performance metrics.

Class	CNN – Precision	Gemini – Precision	CNN – Recall	Gemini – Recall	CNN – F1-score	Gemini – F1-score
Glass	0.96	0.96	0.96	0.90	0.96	0.93
Metal	0.99	0.91	0.96	0.95	0.97	0.93
Paper	0.97	0.97	0.99	0.97	0.98	0.97
Plastic	0.95	0.94	0.94	0.97	0.95	0.95
Average	0.97	0.95	0.96	0.95	0.97	0.95

These findings demonstrate that multimodal AI systems can achieve high levels of accuracy in visual recognition tasks such as waste classification without requiring additional training compared to traditional CNN architectures. The CNN model's epoch-based learning process exhibited a stable structure, while the Gemini model's pre-trained multimodal architecture achieved high generalization success despite varying lighting conditions and complex surface textures. The results demonstrate that hybrid systems (local CNN + cloud-based multimodal models) offer significant advantages in terms of both accuracy and scalability in real-time smart waste management applications.

4. Discussion

This study proposes a smart waste management system integrating artificial intelligence, IoT and mobile technologies. A comparative analysis of the CNN and Gemini models revealed the performance differences between pre-trained multimodal models with classical deep learning architectures. The CNN model achieved 94.5% accuracy after 25 epochs, a performance higher than similar studies in the literature [32, 33]. The Gemini model achieved 97.1% accuracy and an F1-score of 98%, particularly in the paper and plastic classes, without requiring additional training. This is consistent with recent studies [21, 30] showing that multimodal models have higher generalization power compared to classical CNN architectures. Errors in the glass class were due to optical reflections, and similar trends have been reported in the literature [34].

The system's technical architecture focuses not only on model performance but also on a holistic environmental monitoring infrastructure. The sensor layer, built with an ESP32 microcontroller and ultrasonic sensors, measured container occupancy rates in real time. This structure provided low-latency data transfer, similar to the IoT-based waste monitoring systems proposed by Fadhil et al. [35]. The Flutter-based mobile interface allowed users to view the nearest smart bins and increased recycling awareness with a scoring system. In this respect, the study is consistent with approaches that increase user engagement in mobile sustainability applications [36]. The web-based management panel strengthens data-driven management by providing administrators with decision support functions such as occupancy monitoring, fault detection, and route optimization [37].

Consequently, the developed system is not only a high-accuracy classification model but also a sustainable solution that integrates sensor, cloud, mobile and web components. This approach supports the positive impact of the combination of AI and IoT on environmental efficiency highlighted by Bibri et al. [38]. With its low-cost infrastructure, the system provides a scalable, environmentally sensitive and user-centric smart waste management example, laying a strong foundation for future hybrid CNN–Gemini applications.

5. Conclusions

This study proposes an innovative smart waste management system that integrates artificial intelligence, IoT and mobile technologies. The CNN-based model demonstrated balanced classification success with an average accuracy of 94.5%, while the Gemini model achieved 97.1% accuracy without requiring additional training, demonstrating superior performance, particularly in paper and plastic. The results confirm that multimodal AI systems are more robust than traditional CNN architectures in terms of visual generalization capabilities.

The system offers a multi-layered solution with an IoT infrastructure equipped with ESP32 sensor modules, cloud-based data transfer, a user-centric mobile interface and an admin panel. This architecture combines energy efficiency and user awareness in line with environmental sustainability principles. This low-cost, scalable, and real-time system optimizes resource utilization in waste management processes, providing a sustainable framework for smart city applications.

In the future, it is recommended to extend the model to include different waste types, integrate sensor data more deeply with image classification and evaluate hybrid CNN-Gemini architectures for energy efficiency.

Ethics committee approval and conflict of interest statement

This article does not require ethics committee approval and has no conflicts of interest with any individual or institution.

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Author Contribution Statement

All authors conducted the literature review, wrote the manuscript focusing on conceptualization and results presentation, and developed and implemented the code used in this study. Author 1 also supervised the results from the learning models, contributed to writing and editing processes, and conducted a critical review offering feedback for improvement.

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