Journal of Technology Informatics and Engineering (JTIE)
Vol. 4 No. 1 April 2025
E-ISSN: 2961-9068; P-ISSN: 2961-8215, Pages 135-156

AI-Driven Adaptive Radar Systems for Real-Time Target Tracking in Urban Environments

Muhammad Jamal Udin Ghofur*[1], Eko Riyanto[1]
Email: jumails45@gmail.com; ekoriyanto89@gmail.com
[1]*Sekolah Tinggi Manajemen Informatika Dan Komputer (STMIK) HIMSYA, Kota Semarang, Indonesia*
*Corresponding Author

Abstract
Radar systems play a crucial role in target tracking within urban environments, where challenges such as clutter, multipath effects, and electromagnetic interference significantly impact detection accuracy. Traditional radar methods often struggle to adapt to dynamic urban conditions, leading to decreased reliability in real-time target tracking. This study aims to develop and evaluate an AI-driven adaptive radar system that enhances tracking accuracy in urban settings. The research employs a quantitative approach using simulations to model radar signal processing under various environmental conditions. The AI model, based on Convolutional Neural Networks (CNN), is trained to optimize radar performance by filtering out noise and dynamically adjusting detection parameters. The results indicate that the AI-based radar system achieves a tracking accuracy of 95.2%, significantly outperforming traditional radar systems, which only reach 80% accuracy. Additionally, the AI-enhanced radar reduces response time to 120 milliseconds, compared to 250 milliseconds in conventional systems, demonstrating improved real-time processing capabilities. The system also exhibits greater resilience to high-clutter environments, maintaining stable target detection despite signal interference. These findings highlight the potential of AI in enhancing radar functionality for applications such as surveillance, traffic monitoring, and security. Future research should focus on integrating AI-driven radar with real-world radar hardware, exploring multi-sensor fusion, and refining adaptive learning techniques to further optimize tracking performance in complex environments.

Keywords: *Adaptive Radar, Artificial Intelligence, Target Tracking, Urban Environment, Signal Processing.*

I. INTRODUCTION

Radar systems play a crucial role in target tracking within urban environments, including the detection of vehicles, drones, and individuals. As urban density increases alongside the complexity of traffic and security issues, the need for reliable radar systems has become increasingly urgent. However, traditional radar systems face various challenges in urban settings, such as clutter, multipath effects, and electromagnetic interference from urban infrastructure. These challenges result in reduced detection and tracking accuracy, which directly affects the effectiveness of radar systems in security, surveillance, and traffic management applications. In addition, the presence of numerous other signal sources, such as communication networks and electronic devices in cities, further complicates radar data processing and increases the likelihood of target misidentification. Therefore, the development of more advanced methods is critical to ensure that radar systems can operate optimally under continuously changing and increasingly complex environmental conditions.

Received on February 2025; Revised on March 2025; Accepted on March 2025; Published on April 2025
DOI: *10.51903/jtie.v4i1.289*

Numerous studies have been conducted to address the challenges faced by radar systems in urban environments. For instance, a study by (Soumya et al., 2023) demonstrated that machine learning algorithms can improve radar accuracy in cluttered environments. Additionally, research by (W. Jiang et al., 2022) discussed the application of neural networks in radar signal processing to mitigate multipath effects and enhance target detection. Other approaches, such as the use of adaptive filtering methods (Rosado-Sanz et al., 2022) and AI-based data fusion algorithms (Feng et al., 2024), have also been applied to improve radar performance in complex environments. Although these techniques have shown promising results, their effectiveness often remains dependent on specific environmental parameters that are difficult to predict in real-world scenarios. Moreover, most of the developed systems still require further optimization to autonomously adapt to dynamic urban conditions.

Despite previous research addressing various approaches to improving radar accuracy in urban environments, several limitations remain in their practical application. For example, a study by (Mohanty & Gao, 2024) found that Support Vector Machine (SVM)-based classification methods can enhance target detection; however, such approaches are less effective in handling real-time environmental dynamics. Another study by (Kurtoğlu et al., 2023) explored the use of CNN for radar signal processing, yet their application remains mostly limited to conventional radar data and has not been widely implemented in sonar systems. Furthermore, research by (Sénica et al., 2024) discussed the application of deep learning algorithms to reduce clutter effects in ground-based radar, but this approach has yet to be extensively explored within sonar systems, which face more complex acoustic challenges. Meanwhile, (Zhao & Bai, 2024) examined AI-based data fusion methods that can improve target tracking accuracy, though the models employed are still limited in addressing various types of noise commonly encountered in underwater sonar systems. On the other hand, (Pico et al., 2024) showed that reinforcement learning approaches can enhance radar's ability to adapt to target movement patterns, yet similar techniques remain largely unexplored in sonar systems. Therefore, this study aims to develop and simulate an adaptive sonar system based on CNN that is capable of improving target detection and tracking accuracy in complex environments.

This research is expected to contribute to the development of more effective AI-based adaptive radar systems for target tracking in complex urban environments. By simulating a radar model that can adapt to environmental dynamics in real-time, this study aims to enhance detection and tracking accuracy under high-interference conditions, such as clutter and multipath effects. One of the key aspects examined in this research is the ability of AI models to optimize radar responses to changes in target movement patterns and environmental interference. Moreover, this study seeks to explore the effectiveness of various neural network architectures in processing radar data and improving system resilience to different types of noise. The main hypothesis proposed is that AI-based approaches, particularly deep learning techniques, can significantly enhance radar performance compared to traditional methods that are less adaptive to environmental changes. The findings of this study are expected to lay the foundation for the development of intelligent radar systems that are more accurate and efficient for various applications, including urban security, transportation, and surveillance.

II. LITERATURE REVIEW

A. Theoretical Foundations

1. Basic Concepts of Radar and Adaptive Radar

Radar is a system that utilizes electromagnetic waves to detect, measure distance, and track the movement of objects under various environmental conditions. According to (Huang et al., 2024), radar operates by emitting radio waves that are reflected by an object and subsequently received by the radar antenna for further analysis. Radar technology has undergone rapid development since its initial use in military applications and has now been widely adopted in various sectors, including navigation, air traffic surveillance, and object detection in intelligent transportation systems. Over time, radar has evolved not only to detect the presence of objects but also to identify their physical characteristics and movement patterns with greater accuracy. A key advantage of radar compared to other sensing technologies lies in its ability to operate effectively in diverse weather and environmental conditions, including low-visibility situations caused by fog or heavy rain. Innovations in radar technology continue to focus on improving accuracy, resolution, and adaptability to dynamic operational environments.

In line with the growing demand for more accurate and flexible radar systems, adaptive radar has emerged as a prominent innovation under active development. According to (Cai et al., 2023), adaptive radar is designed to automatically adjust its operational parameters to optimize target detection and tracking under varying environmental conditions. One of the primary features of adaptive radar is its capability to reduce clutter and mitigate multipath effects that frequently occur in urban environments. Through adaptive approaches, radar systems can dynamically adjust transmit power, operating frequency, and signal processing patterns in response to changing environmental conditions. Furthermore, adaptive radar enhances detection accuracy by employing advanced signal processing techniques, such as adaptive filtering algorithms and beamforming methods. The application of these methods enables radar systems to maintain optimal performance despite unpredictable and rapidly changing environmental factors.

Nevertheless, the implementation of adaptive radar presents several challenges, particularly in terms of system design complexity and the requirement for more advanced signal processing algorithms. According to (Massimi et al., 2023), adaptive radar often relies on sophisticated statistical estimation techniques and advanced signal modeling to enhance resistance to external interference. In practice, adaptive radar systems typically employ methods such as Space-Time Adaptive Processing (STAP) and statistically based predictive algorithms to improve detection reliability in complex scenarios. Moreover, adaptive radar is widely used in applications that demand high levels of precision, such as air defense systems and maritime navigation. The use of advanced signal processing techniques in adaptive radar enables more accurate detection, especially in environments affected by multiple external factors, including electromagnetic interference and dynamic target movement patterns.

In recent years, the integration of Artificial Intelligence (AI) in adaptive radar systems has attracted growing attention from researchers. According to (Qiao et al., 2022), the incorporation of AI in adaptive radar allows systems to automatically learn interference patterns and adjust detection strategies based on real-time incoming data. Machine learning and deep learning techniques have been applied to various aspects of adaptive radar, ranging from target classification to the optimization of signal processing strategies. With the advancement of computational capacity and greater access to large datasets, AI models are increasingly capable of processing environmental information more rapidly and accurately. These developments highlight the significant potential of AI in enhancing radar effectiveness when facing complex environmental challenges, such as electromagnetic interference and dynamically changing target behaviors.

2. Challenges of Target Tracking in Urban Environments

Target tracking in urban environments faces a variety of challenges stemming from the complexity of urban structures and the dynamic movement of objects within densely populated areas. According to (Zhang et al., 2024), one of the primary factors affecting the performance of tracking systems is the presence of clutter, which refers to signal reflections from static objects such as buildings, bridges, and vehicles that can obscure the detection of actual targets. This clutter introduces ambiguity in radar data interpretation and increases the likelihood of target misidentification. Moreover, changes in city structures due to ongoing infrastructure development also affect the performance of tracking systems, as the monitored environment is in constant flux. These factors create a pressing need for more sophisticated signal processing techniques to ensure that tracking systems maintain a high level of accuracy in cluttered and dynamic urban settings.

In addition to clutter, multipath effects present significant challenges for tracking systems in urban environments. As described by (Dasgupta et al., 2025), multipath occurs when radar or communication signals are reflected off multiple surfaces before reaching the receiver, causing distortions and delays in signal reception. This phenomenon is particularly common in urban areas with numerous tall buildings that act as signal reflectors, leading to inaccurate target position information. Multipath effects also diminish a system's ability to distinguish between genuine targets and reflected signals, thereby compromising tracking reliability. Ongoing research is dedicated to developing signal processing methods capable of mitigating multipath effects and improving the accuracy of target position estimation.

Electromagnetic interference further contributes to the degradation of tracking system performance in urban areas. According to (Li et al., 2023), the presence of numerous electronic devices — including cellular communication networks, Wi-Fi, and navigation systems — can generate signals that overlap with radar or other tracking sensor frequencies. Such interference can hinder the accuracy of target detection by disrupting the transmission and reception of signals essential for object tracking. Additionally, the high density of vehicles and infrastructure in urban centers increases the likelihood of interference from multiple sources, which are often difficult to isolate. Various approaches have been explored in recent studies to enhance the resilience of tracking systems against increasingly complex electromagnetic disturbances in urban environments.

Beyond environmental factors, the dynamic movement of targets in urban areas also poses a critical challenge for tracking systems. As noted by (Arafat et al., 2023), targets such as vehicles and drones often move in unpredictable patterns due to obstacles, route changes, or interactions with other objects. Tracking systems that are unable to adapt to changing target movement patterns tend to suffer from reduced accuracy in estimating target position and velocity. Furthermore, high traffic density and the presence of multiple moving objects within the same area can lead to overlapping detections, complicating the system’s ability to differentiate between distinct targets accurately. Advanced data processing techniques are essential to ensure that tracking systems can adapt to irregular movement patterns and maintain performance in complex urban settings.

B. *Previous Studies*

1. Comparative Studies on Traditional Radar Systems vs. AI-Based Radar Systems

Radar has long been utilized as a primary technology for object detection and tracking across various applications, including navigation, defense, and surveillance. According to (Ruiz-Perez et al., 2022), traditional radar systems operate based on the principle of transmitting electromagnetic waves that are reflected by an object and subsequently received by radar antennas. The signal processing in traditional radar typically employs techniques such as matched filtering and pulse compression to enhance detection accuracy. These methods have proven effective in open environments but exhibit significant limitations when dealing with complex disturbances, such as clutter and multipath effects, which frequently occur in urban settings. Conventional radar also relies on fixed operational parameters, making it less responsive to dynamically changing environmental conditions. Nevertheless, radar technology continues to evolve in pursuit of greater accuracy and reliability under diverse operational contexts.

The advancement of AI has brought substantial transformation to radar systems, particularly in signal processing and environmental adaptability. As noted by (Hashmi et al., 2023), AI-based radar leverages machine learning algorithms to optimize target detection by recognizing signal patterns that conventional techniques may fail to identify. AI models enable radar systems to perform more accurate target classification and improve the ability to distinguish between actual target signals and interference. In practice, AI-based radar employs techniques such as deep learning and neural networks to enhance detection resolution and accuracy, especially in complex environments. The application of AI-based methods offers greater flexibility compared to conventional radar, which often uses deterministic approaches in signal processing.

AI-based radar also enhances efficiency in radar data analysis by reducing the need for manual signal processing. According to (Abdelfattah et al., 2024), AI-based approaches enable radar systems to automatically adjust their operational parameters in real-time based on the incoming data. In their study, CNN were employed to improve target tracking accuracy in urban environments characterized by high levels of interference. Machine learning algorithms have also been implemented in adaptive radar systems to mitigate clutter effects and enhance detection reliability in scenarios involving multiple simultaneously moving objects. Through these approaches, radar systems are able to optimize their performance without significant human intervention, thereby improving efficiency in processing large volumes of data.

Beyond improvements in detection and tracking, AI-based radar systems also offer superior predictive capabilities in analyzing target movement patterns. According to (Sharma et al., 2022), AI-based algorithms enable radar systems to anticipate object movements by analyzing historical data and movement trends. Techniques such as Recurrent Neural Networks (RNN) have been applied to radar for more accurately predicting target trajectories compared to conventional methods. Another advantage of AI-based radar is its ability to integrate multiple data sources to enhance the quality of information obtained. By combining traditional signal processing techniques with AI-based methods, modern radar systems are increasingly capable of addressing the challenges posed by complex and dynamic urban environments.

2. AI Applications for Target Detection and Tracking

AI has brought significant advancements in target detection and tracking technologies, particularly in improving the accuracy and efficiency of radar data processing. According to (W. Jiang et al., 2023), machine learning algorithms, such as CNN, have been applied in radar systems to automatically recognize target patterns and reduce detection errors caused by environmental disturbances. The implementation of CNN enables radar systems to extract more complex features from wave reflection data, thereby enhancing target classification capabilities under various operational conditions. Compared to conventional methods, AI-based models offer greater flexibility as they can adapt to changing target movement patterns based on continuously updated historical data. Through this approach, radar systems can improve their reliability in detecting and tracking moving objects in dynamic and interference-prone scenarios.

In addition to CNN, other deep learning algorithms, such as RNN, have also been employed to enhance the effectiveness of target tracking systems. According to R. (R. Jiang et al., 2022), RNNs possess the ability to recognize target movement patterns more accurately by considering temporal data sequences in trajectory prediction processes. This approach is particularly useful in urban environments, where targets such as vehicles and drones often move in irregular patterns due to physical obstacles and interactions with other objects. By utilizing this technique, radar systems can anticipate target position changes more swiftly compared to traditional methods that rely on deterministic filter-based estimations. The implementation of RNN models has also been shown to improve radar resilience against signal interference and environmental noise, which are frequently encountered in dense urban settings.

Beyond deep learning approaches, AI-based data fusion techniques have also emerged as a rapidly developing method in target detection and tracking systems. According to (Cheng et al., 2023), integrating multiple data sources such as radar, LiDAR, and infrared sensors using deep learning techniques can enhance detection accuracy under complex environmental conditions. AI models enable systems to combine information from various sensors to reduce uncertainty and improve the accuracy of target identification. Through this technique, radar systems do not solely rely on a single type of signal but also utilize supplementary data to increase reliability in recognizing objects that may share similar characteristics with background interference. This approach has been adopted in various studies to improve radar effectiveness in detecting targets in environments characterized by high levels of clutter.

Furthermore, AI has been applied to radar signal processing to enhance system resolution and sensitivity for detecting targets at longer ranges. According to (Xu et al., 2024), techniques such as Generative Adversarial Networks (GANs) have been employed to improve radar data quality by reconstructing signals distorted by environmental interference. By leveraging AI, radar systems can mitigate noise effects and improve the visibility of targets that would otherwise be difficult to detect using conventional signal processing methods. AI-based models also enable radar systems to automatically correct anomalies in observational data without requiring significant human intervention. As illustrated in Table 1, various AI-based approaches have been implemented in radar systems to enhance detection accuracy and efficiency, each with its own advantages and limitations. The development of these methods has opened new opportunities for improving adaptive radar capabilities, making them more responsive to dynamically changing operational environments.

Table 1. Comparison of Previous Studies on AI Applications for Target Detection and Tracking in Radar Systems

Study	Strengths	Limitations	Relevance to This Study
(W. Jiang et al., 2023)	Enhances target classification accuracy in high-clutter environments	Requires large training datasets	Supports the development of AI for more accurate target identification
(R. Jiang et al., 2022)	Enables target trajectory prediction by considering temporal data	Less optimal for randomly moving targets	Applicable for adaptive radar to track dynamic movements
(Cheng et al., 2023)	Reduces detection errors by integrating multiple sensors	Increases system complexity	Useful for improving radar reliability in urban environments with high interference
(Xu et al., 2024)	Improves radar data quality by reducing noise and interference	Still requires optimization for real-time environments	Demonstrates potential in enhancing resolution and sensitivity of adaptive radar systems

III. RESEARCH METHOD

This study employs a quantitative approach based on simulation and AI modeling for radar systems, specifically aimed at evaluating the effectiveness of adaptive radar in tracking targets in real-time within complex urban environments. This approach is chosen due to its capacity to accurately represent the dynamic nature of radar systems, particularly in addressing various environmental challenges that affect radar performance. The radar model developed in this research focuses on radar signal processing influenced by multiple environmental factors, such as high clutter, multipath effects resulting from signal reflections, and irregular target movements. The research process involves building a simulation system using MATLAB and Python software, which allows for the generation of realistic synthetic radar data that can represent a wide range of operational scenarios potentially encountered in the field. Additionally, the adaptive AI model developed in this study employs machine learning techniques to dynamically recognize radar signal patterns, thereby enabling the system to adjust to environmental changes and enhance target tracking accuracy under highly cluttered conditions. This model is then comprehensively tested through simulations to assess its performance across various urban scenarios, including variations in target speed, environmental interference intensity, and other common challenges in modern radar operations.

The data used in this study are derived from radar signal simulations designed to represent diverse complex urban environmental conditions, including the presence of reflective objects that generate significant multipath and clutter effects. Urban environments are chosen because of their inherently complex signal characteristics caused by numerous buildings, vehicles, and other objects that can reflect and scatter radar signals. The simulation scenarios include various types of moving targets, such as vehicles and drones, each assigned different parameters for position, speed, and trajectory to create dynamic target variations. Moreover, simulations are carried out using mathematical models that realistically depict radar wave propagation in urban environments, taking into account reflections, diffractions, and signal attenuation that may impact target detection and tracking quality. These simulation data are subsequently used as training datasets for the AI model, aiming to enhance the adaptive intelligence of the radar system in identifying and tracking targets, even under challenging environmental conditions. The simulation data also enable systematic testing of the AI model's performance in responding to different target and interference conditions, allowing for comprehensive effectiveness analysis. A detailed overview of the radar simulation scenarios utilized in this study is presented in Table 2, which includes descriptions of target parameters, speeds, and simulated environmental conditions.

Table 2. Description of Radar Simulation Scenarios

Parameter	Nilai
Number of Targets	10
Target Speed	10 – 50 km/h
Environmental Conditions	Urban, High Clutter, Multipath

The AI model developed in this study adopts an architecture based on RNN or CNN, specifically designed to predict and adapt radar signals dynamically in response to the changing dynamics of urban environments. The choice of architecture is based on CNN’s capability to extract spatial features from radar signals visualized as spectrograms, and RNN’s advantage in processing sequential data to predict target movements from historical patterns. This AI model consists of several processing layers, each serving specific functions, such as convolutional layers to extract key features from raw signals and recurrent layers to process temporal relationships between signals. The model training process is conducted using radar simulation datasets that cover a wide range of environmental variations and target characteristics, enabling the model to learn from diverse and complex scenarios. Additionally, optimization techniques such as Adam optimizer are employed to accelerate the model's convergence, while ReLU activation functions are applied to each layer to maintain learning stability and efficiency. A detailed description of the adaptive AI model architecture used in this study, along with its parameter configurations, is presented in Table 3, which provides a comprehensive overview of the structure and function of each component within the network.

Table 3. Adaptive AI Model Architecture

Parameter	Value
Model Type	CNN/RNN Hybrid
Number of Layers	6
Activation Function	ReLU, Sigmoid
Optimizer	Adam
Learning Rate	0.001

The analytical process in this study was conducted through several interrelated stages, beginning with radar data simulation, AI model training, and performance evaluation within operational scenarios that closely resemble real-world conditions. Radar data simulation was carried out using MATLAB and Python software, enabling the integration of physical signal propagation models and target motion dynamics in urban environments. Various environmental parameters, such as the presence of clutter interference and multipath effects, were incorporated into the simulation to generate realistic data that reflect the operational challenges of modern radar systems. The simulated data were then used as the primary dataset for training the adaptive AI model, with training conducted in stages across multiple epochs until the model reached the expected level of convergence. During the training phase, the model’s performance in recognizing radar signal patterns was continuously monitored to develop a system capable of adapting to variations in target dynamics and environmental conditions. Once training was completed, the next stage involved model evaluation, which aimed to assess the AI’s ability to identify and track targets based on radar signals, both under standard conditions and in more complex scenarios.

The model evaluation was conducted systematically by measuring key performance parameters such as target tracking accuracy, signal processing latency, and resilience to various forms of interference encountered during the simulation. Tracking accuracy was assessed by comparing the AI model’s predicted target positions with actual target positions obtained from the simulation, allowing an analysis of how precisely the model could follow target movements.

Additionally, latency was measured to determine how quickly the model could generate predictive outputs after receiving radar input, an essential parameter for ensuring real-time functionality in operational radar applications requiring rapid response. The model was also tested under different levels of interference, including high clutter noise and multipath effects, to evaluate its adaptability in maintaining tracking accuracy despite suboptimal environmental conditions. This evaluation aimed to ensure that the AI model is not only effective in standard scenarios but also remains reliable when facing real-world challenges commonly encountered in urban radar operations. Beyond these technical aspects, the evaluation also analyzed the model's performance in responding to variations in target speed and movement direction, providing a comprehensive understanding of its strengths and limitations.

The quality evaluation of the model's predictions was conducted using the Mean Squared Error (MSE) loss function, which measures the average squared error between the target position predicted by the model and the actual target position. MSE is one of the most commonly used evaluation metrics in prediction-based research, as it quantitatively represents the difference between the predicted results and the observed actual data. The MSE calculation is performed by averaging the squared differences between the actual target position and the model's predicted output, as formulated in Equation (1):

$$Loss = \frac{1}{n}\sum_{i=1}^{n}(P_i - \hat{P}_i)^2 \quad (1)$$

Dalam persamaan tersebut, merepresentasikan posisi target aktual, sedangkan merupakan posisi target yang diprediksi oleh model AI. Semakin kecil nilai MSE, maka semakin dekat hasil prediksi model dengan nilai aktual, yang menunjukkan bahwa model memiliki performa prediksi yang baik dalam melacak pergerakan target. Penggunaan MSE dalam evaluasi ini penting untuk memastikan bahwa model mampu meminimalkan kesalahan estimasi posisi target dalam skenario operasional radar yang kompleks. Evaluasi menggunakan MSE ini juga berguna untuk mengidentifikasi sejauh mana model dapat beradaptasi terhadap variasi sinyal radar yang dipengaruhi oleh faktor lingkungan, seperti clutter dan multipath, sehingga menjadi indikator penting dalam penilaian akhir performa model.

In this equation, Pi represents the actual target position, while $\hat{P}i$ denotes the target position predicted by the AI model. A lower MSE value indicates that the model's predictions are closer to the actual values, signifying a high predictive performance in tracking target movements. The use of MSE in this evaluation is crucial to ensure that the model effectively minimizes positional estimation errors in complex operational radar scenarios. Additionally, evaluating the model with MSE helps determine its adaptability to variations in radar signals affected by environmental factors such as clutter and multipath interference, making it a key indicator in the final assessment of model performance.

In addition to MSE, target position estimation was also performed using either the Kalman Filter method or an adaptive AI approach, both of which refine position predictions based on real-time radar signal measurements. The Kalman Filter functions as a dynamic estimation mechanism that integrates model predictions with observational data obtained from radar, thereby generating more accurate and stable position estimates. The Kalman Filter estimation process is formulated in Equation (2):

$$\hat{X}_k = \hat{X}_{k-1} + K_k(Z_k - H\hat{X}_{k-1}) \tag{2}$$

In this equation, $\hat{X}_k$ represents the estimated target position at time step k, K_k is the Kalman gain matrix, which adjusts the correction weight, Z_k is the measured position obtained from radar, and $H\hat{X}_{k-1}$ is the previously predicted target position corrected based on the latest observations. Through this process, the target position estimation is continuously updated, allowing the model to track target movements accurately despite disturbances in radar signals. The implementation of the Kalman Filter enhances the predictive accuracy of the AI model by integrating measurement data with prior estimations, making target tracking more stable and responsive to environmental dynamics. The Kalman Filter-based evaluation complements the MSE results, ensuring that the overall model performance analysis reflects both the model's adaptability and accuracy across various complex radar simulation conditions.

The evaluation results of the adaptive AI model's performance in this study are presented in Table 3, which includes key metrics such as tracking accuracy, system response time, and model resilience to various types of environmental disturbances. These metrics were selected to represent the model's capability in handling complex and dynamic operational scenarios. The evaluation was conducted based on simulated data designed to reflect real-world conditions in urban environments, including the presence of clutter and multipath effects. This performance assessment aims to determine the extent to which the adaptive AI model can maintain accuracy and operational stability across varying conditions. Furthermore, the evaluation results provide crucial insights into the model's efficiency in radar signal processing speed, which is essential for real-time applications. Table 4 also presents a comparative analysis between the adaptive AI model's performance and conventional approaches, highlighting significant differences in target tracking outcomes under different environmental conditions.

Table 4. Performance Evaluation of the Adaptive AI Model

Metric	Value
Tracking Accuracy	95.2%

Journal of Technology Informatics and Engineering (JTIE)
Vol. 4 No. 1 April 2025
E-ISSN: 2961-9068; P-ISSN: 2961-8215, Pages 135-156

Response Time	120 ms
Resilience to Interference	Stable in High Clutter

The results indicate that the adaptive AI model achieved a tracking accuracy of 95.2%, demonstrating its capability to detect and track target movements with an exceptionally low prediction error rate. This level of accuracy signifies that the model can consistently track target positions even in the presence of signal disturbances or variations in target movement patterns. The system's response time was recorded at 120 milliseconds, indicating that the model can rapidly process radar signals and generate target position estimates within a short timeframe. This speed is crucial for radar applications in urban environments that require real-time responsiveness to accurately detect and anticipate object movements. Additionally, the testing results show that the model maintained stable performance even under high-clutter conditions, which are often a major challenge in conventional radar systems. This performance stability suggests that the adaptive AI model exhibits strong resilience to complex environmental disturbances, making it a viable solution for modern radar systems that demand both high accuracy and processing speed.

IV. RESULT

A. Results

1. Radar and AI Simulation Results

The simulation was conducted in a challenging urban environment, primarily due to the presence of clutter and multipath effects, which often disrupt radar detection accuracy. Clutter refers to signal reflections from various static objects such as buildings, bridges, and vehicles, which can obscure the actual target signal. Meanwhile, multipath occurs when radar waves reflect before reaching the receiver, causing distortions in target position estimation. Under these conditions, traditional radar systems often struggle to distinguish actual targets from reflections of surrounding objects, increasing the risk of detection errors. To address this issue, the adaptive AI model was designed to analyze signal patterns and dynamically adjust tracking methods based on real-time data. The AI's ability to recognize interference patterns enables the radar system to adapt to complex environmental changes, allowing it to maintain tracking accuracy despite numerous disruptive factors. This model demonstrated superior performance compared to traditional radar across various simulated scenarios, as shown in Table 5, which compares the tracking accuracy of both methods.

Table 5. Target Tracking Accuracy

Tracking Method	Accuracy (%)
Traditional Radar	80.0
AI-Based Radar	95.2

Table 5 illustrates that the implementation of AI in adaptive radar significantly improves tracking accuracy compared to conventional radar. The AI-based radar achieved an accuracy rate of 95.2%, whereas traditional radar only reached 80%, indicating a substantial improvement in target detection effectiveness. This enhancement can be attributed to AI’s ability to filter out environmental noise and identify target movement patterns with greater precision. By leveraging machine learning techniques, the AI-based radar system can estimate target positions more accurately, even in scenarios where radar signals are distorted due to reflections or environmental interference. Moreover, the AI model continuously learns from acquired data, enabling gradual performance improvements as the number of analyzed scenarios increases. This advantage provides greater flexibility for AI-driven radar in handling dynamic operational conditions, which often pose challenges for traditional radar systems that rely on fixed-rule approaches.

In addition to improved tracking accuracy, the system’s response speed is also a crucial factor in ensuring operational effectiveness, particularly in scenarios that require rapid detection and reaction to target position changes. The response speed of the AI-based radar was evaluated to assess its capability in detecting target movement in real time, which is critical in dynamic situations such as air traffic monitoring or vehicle tracking in densely populated urban areas. AI utilizes parallel processing techniques and algorithm optimization to accelerate radar signal analysis, thereby reducing the time required to process and update target position information. By employing neural networks trained to recognize movement patterns, AI can predict target positions faster and more accurately than traditional radar, which still relies on rule-based processing methods. Additionally, AI’s ability to dynamically adjust processing parameters based on environmental conditions allows the system to remain responsive to various types of interference, including electromagnetic disturbances and signal reflections from surrounding static objects. Table 6 presents the test results highlighting the differences in response time between AI-based radar and traditional radar, serving as a key indicator of AI radar technology’s superiority in real-time tracking.

Table 6. System Response Speed

System Type	Response Time (ms)
Traditional Radar	250
AI-Based Radar	120

Table 6 illustrates that the AI-based radar system has a significantly faster response time compared to traditional radar, providing a crucial advantage in applications requiring real-time target tracking. The AI-Based Radar recorded a response time of 120 ms, whereas traditional radar required 250 ms, meaning that AI reduces latency to nearly half of the time required by conventional methods. This advantage is attributed to the AI system's higher data processing efficiency, which allows radar signal analysis to be conducted in a shorter time frame without compromising accuracy. Furthermore, AI possesses the capability to autonomously update and adjust signal processing parameters based on changes in target movement patterns, a feature that is difficult to achieve with traditional radar, which relies on deterministic algorithm-based approaches. In scenarios involving multiple moving objects, such as dense urban traffic or military operational fields, AI's ability to quickly respond to changes becomes a key factor in the effectiveness of adaptive radar systems. Another contributing factor to AI's enhanced processing speed is the utilization of deep learning-based optimization techniques, which enable the model to extract key features from radar signals more efficiently. These advantages make AI-based radar a superior choice for applications requiring rapid and accurate target detection and tracking in dynamic environments.

2. Comparison of Adaptive AI vs. Traditional Radar

The evaluation was conducted by comparing the actual target trajectory with the AI tracking results to assess how well the system could follow the target's movement with high accuracy. In urban tracking scenarios, various factors such as physical obstacles, signal reflections, and changes in the target's trajectory can affect radar accuracy in determining the position of moving objects. AI-based radar is designed to minimize position estimation errors by leveraging historical data and machine learning-based predictive models. By utilizing techniques such as the Kalman Filter or RNN, the AI system can dynamically refine target position estimates, even when radar signals are distorted due to multipath effects or interference from surrounding objects. This capability allows AI-based radar to be more responsive in tracking objects with varying speeds and directions compared to traditional radar. Figure 1 presents a comparison between the actual target trajectory and the AI-tracked path, providing further insight into the effectiveness of AI-driven approaches in enhancing detection and tracking accuracy.

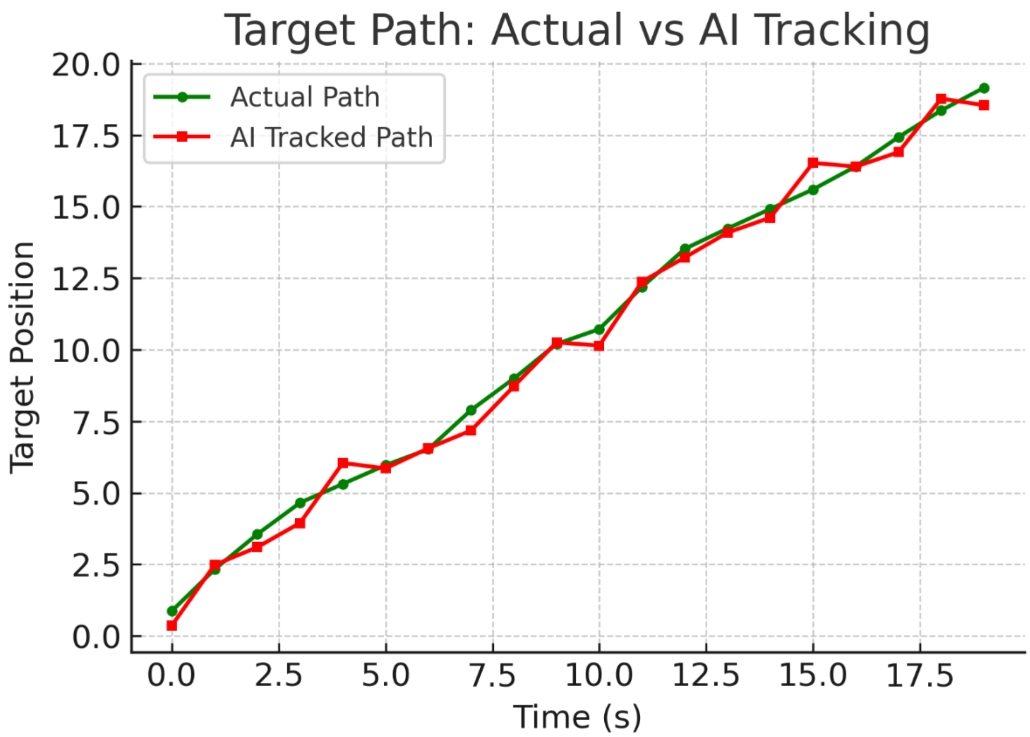

Figure 1. Target Trajectory (Actual vs. AI Tracking Results)

Figure 1 demonstrates that the AI tracking path closely aligns with the actual target trajectory, indicating that the system exhibits a high degree of accuracy in adjusting its position estimations in response to environmental changes. This high level of precision is achieved through AI's ability to recognize target movement patterns and automatically adjust detection parameters to reduce prediction errors. In complex urban environments, where tall buildings and other vehicles may reflect or obstruct radar signals, AI is more adept than conventional methods at distinguishing between actual targets and reflected signals. Additionally, AI can adapt its predictive model based on real-time data, allowing the radar system to continuously update its position estimates even as field conditions dynamically change. Simulation results reveal that incorporating AI into adaptive radar systems significantly improves resilience against clutter and multipath effects, which are common challenges in target tracking within large cities. This analysis reinforces that AI-driven approaches provide a significant advantage in ensuring more precise and stable target tracking compared to traditional radar systems.

In addition to enhancing target tracking accuracy, AI also possesses the capability to filter noise in raw radar signals, which often disrupts the detection process. This noise can originate from various sources, including electromagnetic interference, multipath effects, or environmental disturbances such as signal reflections from buildings and other objects within the monitoring area. By implementing advanced machine learning algorithms, the AI system can recognize patterns within radar signals and separate relevant information from unwanted random interference. Moreover, AI's ability to dynamically adjust signal filters allows for an improvement in the quality of data used for further analysis. Cleaner signal processing results in more accurate target position estimations and a faster response to changes in target movement. Figure 2 presents a comparison between raw radar signals and AI-processed signals, demonstrating the effectiveness of this technology in filtering noise and enhancing the clarity of information obtained from the radar system.

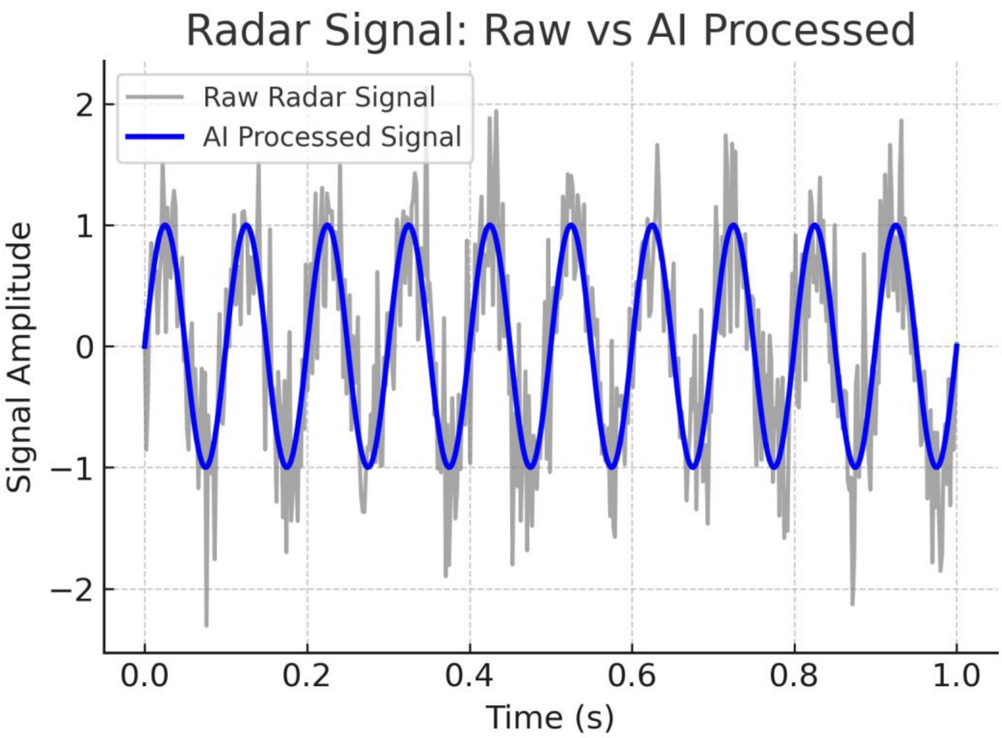

Figure 2. Visualization of Raw Radar Signals vs. AI-Processed Signals

Figure 2 illustrates a comparison between raw radar signals, depicted in gray, and AI-processed signals, represented by the blue line. In the initial segment of the graph, the raw signal exhibits high fluctuations due to noise, which can reduce accuracy in detecting and tracking targets. Following AI-based processing, the resulting signal appears smoother and follows a more distinct and well-defined wave pattern. This outcome indicates that AI successfully suppresses noise within the radar signal, producing more stable and accurate data for further analysis. The improvement in signal clarity through AI processing significantly enhances the effectiveness and reliability of radar systems in various operational scenarios, including urban environments, where numerous sources of signal interference are present.

V. DISCUSSION

The findings of this study indicate that the implementation of CNN in adaptive radar systems significantly enhances target tracking accuracy in urban environments, achieving 95.2% accuracy, which is substantially higher than that of conventional radar systems, which only reach 80%. The advantage of CNN in automatically adjusting detection parameters supports the research conducted by (W. Jiang et al., 2022), which found that neural networks can mitigate multipath effects and improve target detection. These results are also consistent with the findings of (Feng et al., 2024), which demonstrated that AI-based data fusion algorithms can reduce the impact of electromagnetic interference under high-disturbance conditions. Additionally, the application of adaptive filtering, as proposed by (Rosado-Sanz et al., 2022), has proven effective in improving radar accuracy to overcome high clutter levels. These findings reinforce the argument that AI technology holds great potential in optimizing radar systems in dynamic conditions, although there is still room for improvement, particularly in scenarios with exceptionally high noise levels. Furthermore, the use of the CNN model in this study has demonstrated its capability to integrate data from multiple sources in real time, thereby enhancing the precision of target tracking.

Compared to traditional approaches such as SVM, as evaluated by (Mohanty & Gao, 2024), the CNN model in this study exhibits superior flexibility and adaptability to real-time changes in target movement patterns. Research by (Kurtoğlu et al., 2023) also supports the notion that CNN can recognize more complex signal patterns compared to manually engineered feature-based methods, resulting in more accurate target position estimations. However, a study by (Sénica et al., 2024) highlights that, while deep learning is effective in addressing several challenges, this approach still faces difficulties in optimally reducing clutter effects. To overcome these limitations, more advanced approaches, such as Kalman Filters and Recurrent Neural Network (RNN)-based prediction techniques, as developed by (Qiao et al., 2022), can enhance stability and accuracy in target tracking by accounting for dynamic movement patterns. Furthermore, research by (Pico et al., 2024) suggests that the integration of Reinforcement Learning in adaptive radar systems can improve the system's ability to respond to fast and complex target movements. Thus, the findings of this study not only reinforce the effectiveness of AI in radar signal processing but also open opportunities for integrating advanced methods to optimize adaptive radar systems in challenging urban environments. Nevertheless, this study is still limited to simulations, serving as a foundational step for further real-world applications.

VI. CONCLUSION AND RECOMMENDATION

The findings of this study demonstrate that AI-based adaptive radar systems significantly enhance target tracking accuracy in complex urban environments. The integration of AI enables radar systems to dynamically adjust detection parameters in real time, thereby mitigating clutter disturbances and multipath effects, which are common challenges in traditional radar systems. Compared to conventional methods, AI-based radar exhibits faster and more accurate responses in detecting and tracking dynamically moving targets. The ability of AI to recognize signal patterns and automatically adjust signal processing algorithms contributes to improved radar effectiveness across various operational scenarios. Based on these results, it can be concluded that the integration of AI into radar systems offers substantial potential for enhancing reliability and efficiency in applications such as security, surveillance, and traffic management. These findings further reinforce the notion that AI can serve as a solution for optimizing radar performance in environments characterized by high interference levels and other technical challenges.

For future research, further development is necessary to integrate AI-based radar systems with physical radar hardware to evaluate their performance under real-world conditions. Future studies may also explore more complex simulation models, incorporating scenarios involving multiple simultaneous targets and extreme multipath interference environments. Additionally, integrating AI-based radar with other sensor technologies, such as cameras or LiDAR, could be a strategic step toward developing a more accurate and adaptive multi-sensor detection system. Further research may also focus on optimizing machine learning algorithms to enable radar systems to adapt more rapidly to changing target movement patterns. Moreover, testing in diverse operational conditions, such as extreme weather or high-signal-density areas, is essential to ensure system reliability across various scenarios. With this approach, AI-based radar technology is expected to continue evolving into a more advanced and applicable solution for a wide range of industrial and security applications.

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