Research Article

An Artificial Intelligence Mechanism for the Prediction of Signal Strength in Drones to IoT Devices in Smart Cities

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Drones, the Internet of Things (IoT), and Artificial Intelligence (AI) could be used to create extraordinary responses to today’s difficulties in smart city challenges. A drone, which would be effectively a data-gathering device, could approach regions that become complicated, dangerous, or even impossible to achieve for individuals. In addition to interacting with one another, drones must maintain touch with some other ground-based entities, including IoT sensors, robotics, and people. Throughout this study, an intelligent approach for predicting the signal power from a drone to IoT applications in smart cities is presented in terms of maintaining internet connectivity, offering the necessary quality of service (QoS), and determining the drone’s transmission range offered. Predicting signal power and fading channel circumstances enables the adaptable transmission of data, which improves QoS for endpoint users/devices while lowering transmitting data power usage. Depending on many relevant criteria, an artificial neural network (ANN)-centered precise and effective method is provided to forecast the signal strength from such drones. The signal strength estimations are also utilized to forecast the drone’s flight patterns. The results demonstrate that the proposed ANN approach has an excellent correlation with the verification data collected through computations, with the determination of coefficient $R^2$ values of 0.97 and 0.98, correspondingly, for changes in drone height and distances from a drone. Furthermore, the finding shows that signal distortions could be considerably decreased and strengthened.

1. Introduction

Drones are often referred to as unmanned aircraft systems. The drone is a flying robot, and it can be remotely controlled or flown automatically using software-controlled systems. It works in conjunction with sensitive devices and the global positioning system (GPS). Drones are now in demand for testing and multiple applications because of their versatility and capability to be used in a broad variety of applications, such as control, security, observation, and the rapid surveillance of inaccessible terrain. Furthermore, it is an alternative technology that enhances the ability of first responders to reach the areas of environmental disaster and carry out rescue operations. It can assist in emergency preparedness situations, such as medicine distribution, forest fire extinguishing, vital infrastructure preservation and testing, coastal surveillance, and police upgrades, and it can help meet the public safety standards of urban areas.
There are many different types of novel technologies that can be accessed by drones, depending on the type of activities being performed. Nonetheless, they are commonly used in the military. Drones are now used in a variety of areas, including commercial and civilian applications, such as disaster and crisis management, surveillance, hostility, rescue and search operations, temporary relay networks, civil defense, remote and agriculture sensing, wind assessment, and so on. Also, the most advanced applications of drones nowadays are their participation in smart urban areas. Real estate, infrastructure, communications, and marketing are some of the businesses offered in Smart Urban. The advantages of Smart Urban extend to everybody, including companies, people, government, ecology, and more [1]. Because of their agility, mobility, and adaptability, drones are often used in a variety of attributes. Drone user tools play a key role, especially in packaging delivery, remote sensing, and access management. As flying drones require cellular infrastructure, low-latency communications and seamless connectivity are achievable. The 5th generation new radio and extensive term evolution cellular technologies are capable of providing robust security and management over a wide variety of high-speed, secure wireless connections to drone operations.

Compared to fixed terrain base stations, such as WiFi for information gathering, drones have the advantage of being quick to use. They can also get closer to IoT devices, capture large amounts of device data (high data rate), and provide flying communications. Moreover, the drone system enables LoS to reduce shadow and signal interference. Furthermore, connection and range concerns are often a barrier to gathering accurate information from the IoT framework. because of its flexibility, mobility, and strong communication connectivity, the drone is able to go to IoT device sites and create energy-effective networks, minimizing IoT device power consumption. The data obtained will then be sent to the nearest base station (BS) [2]. The link between public security and the Internet of Things (IoT) was explored, and the IoT-based Smart City classification was presented. The usage of IoT technology in urban cities will lead to variations and developments in security, economy, public utility, monitoring, and transportation [3]. The Smart City is a complex structure, largely built by Communications and Information Technology (ICT), with the aim of making metropolitan residences more desirable, practical, and ideal locations for corporate growth. App developers, professional firms, citizens, government, and open specialized companies inquire about networking, and staging engineers are key stakeholders in the Smart City. Figure 1 depicts the various services of smart cities. Furthermore, the smart urban cycle includes many ICT innovations, phases of development, maintenance and management sites, communal applications, and specific financial and social KPIs (key performance indicators). As a result, IoT platforms play an important role in building a broader multifaceted foundation [4].

Smart urban initiatives can accurately solve the problem of ensuring a greener environment by developing and implementing low carbon emissions technology. Many governments around the world (e.g., Japan, USA, EU, and others) have planned and implemented smart city plans to successfully address any growing difficulties. To satisfy the expectation of a smart city, it is essential to properly control the analysis of the effective use of communication and information technology data, communication systems, and the efficient use of a complicated strategy to achieve the safe and smooth functioning of a modern city [5]. As per statistics, the worldwide urban population is anticipated to reach 70% or 75% by 2052, depending on the source. This rate of urbanization will have significant effects on the environment, administration, and the safety of towns. Several governments have advocated the notion of urban cities to properly control resources and enhance energy usage to deal with the dramatic rise in urbanization [6]. The concept of smart cities starts with the improvements needed to provide more efficient and timely services to residents. To solve this problem, drones offer tremendous potential for rapid transition from early planning to the real universe, as well as assist urban dwellers in improving living conditions. The timing of creating automation for corporate and average citizen activities requires an understanding of the specifics of certain requirements set out for their owners. Traffic flow management, which is organized in urban areas, requires the automata to be gradually solidified with a precise route design and be more sophisticated than other methods. As the metropolitan population is dense, automatons will be equipped with attack sensors, GPS data, and computerized maps [7]. Figure 2 shows the architecture of IoT (Internet of Things).

The technologies of smart city opportunities vary from the field of smart cities are the autonomous vehicles (AV), robots, big data, 5G, 3D printing, blockchain, cloud computing, Internet of Things (IoT), virtual reality (VR), artificial intelligence (AI), and digital twins. While some of these techniques are important in making human cities smarter, AI paired with this technology has considerable promise to report the current urbanization concerns. Moreover, AI is often regarded as the most revolutionary innovation of humans [8]. The Internet of Things (IoT) is a modern management movement in the field of information technology, and it has the potential to revolutionize many human activities. There are many approaches to using this method that have been researched and used around the world. Scientists are identifying cases where IoT principles are used for fully automated operations. The Internet of Things (IoT) is the greatest essential and noteworthy component of maximum smart urban implementation that is capable of generating large amounts of data [9]. IoT devices, including cameras and other sensors, are scattered across many smart city applications to gather information about the surrounding atmosphere. These devices are often little and have a low battery lifespan, and hence, they cannot
transfer signals over long distances. As a result, drones are essential for energy savings, and QoS is maintained to collect information from IoT devices installed in a wide range of applications [10]. Because IoT-based techniques have been extensively employed in smart cities, whereby vast volumes of information are created and sent, it is challenging to properly comprehend the information from a complicated world and deliver efficient operational measures in response. The artificial neural network is a potentially developing method that takes a long-term objective into deliberation and provides the greatest system mechanism for time-variant system dynamics. Figure 3 shows the Internet of Things application in various fields.

Among such large and complex pieces of information, it is difficult to accurately select the most efficient and accurate functions. To achieve optimal judgment, modern approaches, including machine learning, artificial intelligence, and deep reinforcement learning, can be used to make highly relevant evaluations of massive data. Previous strategies take into account the need for full-time targeting and lead to better or closer control options. The accuracy and reliability of the above procedures could be additionally improved by raising the quantity of training data used to improve their learning skills, and consequently, the ability to make their own decisions [11]. The artificial neural network approach is more effective and precise for predicting the drone signal strength based on drone altitude, path losses, and many other related features that have been described. The effect of ANN on human everyday lives is growing with each day. The basis of daily human employment is fast changing in response to ANN, which is influencing the conventional perspective on human thought and responses to the environment. How could new legislation be drafted to guard the present and coming generations from the harmful consequence of ANN, although maximizing its helpful consequences to humanity? Moreover, how can AI-assisted instructions and rules be considered to promise economic and social development? The study has developed an effective criminality detection approach for a smart urban area based on neural networks. Likewise, the study presented a machine learning-based framework that may be utilized to forecast incidents and provide responses prior to their
occurrence [12]. Figure 4 depicts the working arrangement of an artificial neural network (ANN).

The potential benefits of ANN for urban areas are still deliberated in the literature, especially in the setting of urban cities, which are facilitated by strategies for delivering community, technology, productivity, improvement, livelihoods, sustainability, well-being, convenience, effective management, and planning. Although there are a number of papers on the subject, no scholarly book exists that gives a complete evaluation of the expanding literature. This study analyzes the literature to explore how ANN can help build urban cities. This study uses a complete literature review on the issue of “ANN and Smart City” as its methodological technique. ANN is an excellent tool for managing and analyzing a wide range of data to facilitate business choices. It is especially true when combined with IoT, which is an internet-based technology that enables a wide range of sensors to communicate in a network without human involvement. Using technologies, including blockchain, fog computing, and cloud storage, AI has the ability to capture, store, and distribute data, automating the data management process and eliminating demand intermediaries, thereby maximizing profits. Moreover, AI can expand the constancy and performance of IoT devices, resulting in better network connectivity. As a result, information exchange will increase and innovation and entrepreneurship will be encouraged [13]. ANN can be used to identify patterns in databases, improve the information management process, enhance the complete performance of the information managing system, and recognize cyber-attacks and other inefficiencies. The use of ANN is feasibility to do away with the necessity for people to repeatedly engage in commercial activities, mainly trusting on care, decreasing potential costs, and releasing capital to the most creative or advanced industries [14].

2. Related Works

The incredible technical advancements of the twenty-first century have brought a plethora of intriguing and practical answers to nearly any issue imaginable by man. Investigators have been driven to the IoT technology in current years because its trends have shown to make people’s lives easier, cities smarter, and the planet a good residence for living. Nevertheless, technological advancement necessitates a large amount of energy, as well as the development of massive amounts of e-waste and toxic pollutants. The study examined the approaches and tactics that can increase life performance and make the world better, greener, more sustainable, and safer to reside in. The study particularly emphasized green IoT as a means of establishing a smart and sustainable environment via effective resource usage, reduced energy consumption, reduced pollution, and waste creation. This study is an excellent resource for anybody interested in learning about the most recent trends on the subject of green IoT. The study also showed the enabling ICT resources (WSN, RFID, M2M, communicating network, and internet) that have significantly improved the capabilities for green IoT. Concerning the significant elements of ICT, all objects nearby people will be cleverer to accomplish any activities individually, enabling different kinds of green contacts among objects and humans, as well as amongst the objects themselves, whereby the bandwidth consumption is the most, harmful pollution is minimized, and energy demand is ideally lowered. Another aspect of this study in which researchers highlighted the critical utilization of green IoT for the modern and green world was a study of the
various diverse fields of green IoT in multiple industries. The study also outlines the obstacles and potential upcoming research areas in the route of green IoT development for a smarter and greener environment. The research focused on developing green IoT and creating cities better through the use of smart systems for power effectiveness. Yet, the integration of drones and IoT devices in this research has not been realized to its maximum potential [15].

Because of great flexibility and cheap cost, unmanned drones now play an essential part in a wide range of applications. One of the most important tasks in achieving dependable UAV connectivity is to examine the propagation properties of the channel. In this research, the study offers machine learning-based route loss models for the UAV air-to-air (AA) case. A ray-tracing program is used to create specimens for several paths in a common urban setting, and variable Tx and Rx UAV heights are properly considered. On the basis of the training phase, two machine-learning techniques, namely random forest and KNN, are used to develop a predictive model. The estimated accuracy of trained models is evaluated on the testing dataset using metrics, including root mean square error and mean absolute error. Simultaneously, two estimation techniques for evaluation are offered. It is demonstrated that machine learning-based systems may deliver good predictive performance while maintaining appropriate computing performance in the AA situation. Furthermore, random forest beats all other systems and has the lowest error rates. Additional research is being conducted to assess the effects of five distinct factors on route loss. It is shown that route accessibility is critical for path loss. The outcomes revealed that route accessibility is the most important factor. Propagation distances and altitude have also had a significant impact. Because UAV AA communications is a new dynamic, channel modeling and route loss estimation in such a situation are still in their early stages. Several machine learning-based models, such as ANN and SVR, should be introduced in ongoing growth. Special techniques should also be considered to validate the generalization characteristics of these systems. Lastly, assessment studies in the AA case should be performed. Further data is predicted to increase the effectiveness and affordability of machine learning-based route loss predictions [16].

Drones in flight may be utilized for a variety of purposes and services, ranging from monitoring to package transportation. Cellular systems must offer dependable wireless access to drone user devices to guarantee the strong performance and safety of drone operations. Currently, they are developing mobile networks that have been mainly created and improved for supplying ground user equipment, producing flexibility, and resolving cloud trouble. In this study, a novel handover method for a cellular connecting drone system is designed to support strong wireless capabilities and mobility support for drone-UEs. HO choices are continuously improved using a Q-learning algorithm, employing methods from reinforcement learning, to deliver effective flexibility and scalability in the sky. The research demonstrated how the network may balance the number of HOs with the acquired signal intensity by altering the weighting of these parameters in the optimization method. The simulated findings show that, as compared to the baseline HO method in which the drone continuously links to the greatest cell, the suggested technique can considerably decrease the number of HOs while retaining a stable connection. Continued studies might go into a number of different areas. To begin, the current architecture only analyzes drone motion in 2D. Allowing 3D drone movement will be a logical expansion. The testing region and flight paths examined in this work are quite small. It will be instructive to see if the results hold true for bigger testing locations and longer flight paths with a broader pool of potential cells. The suggested method and simulation results depend on the RSRP measure. Another noteworthy involvement will be the addition of new variables to the model [17].

With an explosive increase of multiple drone operations ranging from infrastructure observation to package delivery options, integrating UAS with smart city transportation networks has become a true challenge that necessitates completely innovative and maintainable (secure, safe, with minimal ecological power and lifespan cost) strategies. The
fundamental goal of this suggested alternative is to define paths as desirable and ordered trajectories and execute them autonomously. The worldwide GPS common set with accompanying GIS mapping provides the airspace structure and fixed paths. The idea implementation necessitates additional research and answers, such as drone trajectories monitoring, via an autonomous trajectory tracking control scheme and autonomous conflict identification, resolution, safe drone following, and formation flight choices. The study presents such hypothetical designs and provides some validation testing results. Drones will be linked to the agencies and a planned trajectory to provide them with accurate data on the trajectory and corridor. The agencies will create predetermined or preferred paths using trajectories components. Drones may employ traditional GPS, acoustic, infrared, and optical sensors for location and sophisticated navigation. The accurateness is achieved by including specific indicators in the infrastructure. The concept of safe drone use in a city environment and the potential for secure integration of drone traffic into the overall intelligent urban transportation system. In fact, the application of this notion necessitates more practically to employ a diverse range of methodologies [18].

Urban areas utilize modern technologies of information and communications to increase the effectiveness of urban services and power efficiency. Drones, in this aspect, may be used to assist multiple services, including traffic analysis, selection/rescue, and monitoring, by connecting with a variety of smart items, including sensors. Protecting such interactions is essential in making sound judgments, and it necessitates the use of effective cryptographic techniques. Moreover, the development of these protocols should take into account the flexibility and short battery life of drones and the restricted resource of smart devices. This study presents a set of cryptography algorithms for dealing with 3 different transmission schemes, such as one-to-many, one-to-one, and many-to-one. Researchers develop an efficient certificateless signcryption tag key encapsulation mechanism (eCLSC-TKEM) for one-to-one encryption that provides a verified key exchange protocol, nonrepudiation, and user revocation. By decreasing the computational cost of the smart object, eCLSC-TKEM decreases the time necessary to create public keys between a drone and a smarter object. The study presents a certificateless multi-recipient encryption method for one-to-many communication that permits a drone to effectively produce sensitive data to several smart devices. The study offers a certificateless data aggregation mechanism for many-to-one, which enables drones to quickly gather information from hundreds of smart things. In addition, for effectiveness, the study presents a dual channeling mechanism that enables several smart objects to perform this protocol at the same time. eCLSC-TKEM is evaluated using parking guidance managing testing. It also demonstrated the GPU-accelerated effectiveness of CL-MRES and CLDA on a board with a graphics-processing section. To perform properly, this approach necessitates application improvements and specialized client-server apps [19].

The present biometric systems in most drone-based apps suffer from real-time lag difficulties and security weaknesses for attackers. To solve such difficulties, the study proposes a low-latency safe security mechanism for drones in Smart Urban based on the blockchain. The research utilizes a zone-based design in drones’ networks and a customized decentralized consensus termed as drone-based delegation proof of stake for drones between areas in a modern city, which does not need reauthentication. The suggested architecture intends to improve safety and minimize latencies on the Internet of Drones. Furthermore, the study compares the system framework to existing peer models initially done for IoD to establish its reliability and scalability authentication capacity. The testing findings clearly indicate that, compared to the existing pattern, the suggested architecture not only has a small packet delay, maximum throughput, and low end-to-end delay but also could identify 97.5 percent of hostile drone assaults while flying [20].

2.1. The Mechanism for Signal Propagation between Drones and IoT Systems. A drone is operated and kept flying in a certain direction. It receives data from operators on the surface who monitor the drones as they go. They recognize individual objects and assist drones in reaching precise positions using signal power. Multiple processes affect the traveling signals in distance. The analysis of signal strength is perhaps the most significant aspect of transmission. Such events have an impact on the signal intensity amongst drones, agents, or IoT systems on the surface. As a result, the signal would achieve the target very weakly [21]. As a result, when constructing the transmission and receiver, certain occurrences must be factored into the equation. The signal intensity is affected by the drone’s altitude, length, and route losses. The signal route losses occur as a result of the information taking a multipath and arriving at varying times. The signals route losses vary depending on the influence of the environment. Because of a major towering building in a city, the transmission distance is extremely high [22]. Furthermore, it is minor in the suburbs and even smaller in rural areas. Reflections, refraction, and dispersion, as well as transmission weakening, are all the effects of the surroundings. Whenever a propagated signal collides with a large-scale object, it is called reflection. Whenever a propagated signal channel is interrupted by a sharp object between the transmission and reception, the transition occurs.

The application of drones aiding IoT devices is depicted in Figure 5. When a propagating signal deviates from such a direct route, scattering occurs. As a result, the scattered signals are caused by a curved surface and a small thing. The effective communication among drones and surface operators or IoT systems and the base center units is determined by characteristics, including radiation intensity and signal power [23]. The signal strength and radiation strength are affected by the covering community and surrounding environment. The possibility of covering and the total rates for various IoT devices are delivered by drones. Additionally, installing drones improves wireless transmission availability. A stable channel among the drone and ground-based facilities is required for every drone-based service to be effective [24]. As a result, the drone is among the aerial robots that have piqued people’s curiosity for a range of smart cities.
It is not simply a plane in the sky. It is a computer with a network infrastructure that includes a space component, a ground segment, and a communications system that connects both.

2.2. Signal Strength. To preserve signal strength at the receivers, the signal strength between the access point and smartphone should be greater than the significance level. Similarly, the signal strength should not be too great since it will generate a cochannel interfering with some other smartphone channels that use the same frequencies. The intensity of the transmitted power is affected by route losses, as well as transmission and reception settings. The strength of the received data determines the level of the call. The signal strength is affected by external factors and median degradation [25]. On the one side, essential propagation models show that the total RSS strength drops nonlinearly as transmission distance. Path loss, on the other hand, refers to how much signal intensity is lost throughout transmission from the transmitter and the receiver. The propagation model suggests the average RSS for transmission and receiver based on detachment spacing and the variance of signal strength in a specified place. They seem to be suitable for determining the transmitter network coverage of a transmitter and characterizing signal strength more than a significant disconnection distance between transmission and receiver. Signal distortion and route loss can be predicted using propagation algorithms. The propagation path losses that are generated across all losses faced by the signals throughout their transmission from the base station (BS) towers to the smartphone network or mobile station (MS) are critical restricting elements in coverage estimation [26]. The knowledge of path loss could be utilized to control system efficiency or coverage. The Hata option is designed to anticipate the propagation characteristics by investigating and analyzing the HAP propagation path. The Hata concept is a path loss that is based on empirical data.

\[ I_p(b^d)X + Y \log(d_i) \]  

Here, \( d_i \) is the distance in kilometers and \( X \) is the constant loss, which is determined by the frequencies \( f \) in megahertz, and therefore, it is given in equations (2) and (3).

\[ X = 70.62 + 18.25 \log(f) - 14.71 \log(b_h) - x(m_h), \]  

\[ Y = 51.8 - 5.42 \log(b_h). \]

The altitude of the ground station antennas in meters is given by \( b_h \). The elevation of a wireless station antenna in meters is measured in \( b_h \). In Bdm, \( x(m_h) \) is the association coefficient, which is provided in the following:
\[ x(m_h) = [2.1 \log(f_r) - 1.8]m_h - [1.43 \log(f_r) - 0.7]. \quad (4) \]

QoS is a term that describes how well a system performs, and it is used to assign a set of characteristics that represent measurable qualitative characteristics. Path loss is an important factor in improving wireless communication’s QoS.

Signal strength out of a drone at various ranges: in the first case, the drone position is given. Use the ANN model for forecasting signal strength out from the drone distribution point. Based on a fixed drone placement, the ideal coverage area should be determined along with the manner in which IoT sensors attached to the drone while maintaining excellent QoS should be maintained. IoT devices’ communication power would be lowered as a result.

The drone’s height is considered to remain constant in this case, and the transmitted signal from the drone is calculated depending on the distance between the drone and the floor IoT devices [27]. The approach is depicted in Figure 6. These forecasts were important for calculating a drone’s range and the number of drones necessary to keep maximum coverage and ensure QoS in a particular geographical region.

2.3. Drone Coverage and Movement. Among a drone’s constraints are its operating height. Signal strength is important for determining the appropriate height for a drone’s flight route, and IoT devices seem to be more approachable throughout this area. The drone should span every IoT device in the approach and interact through a significant relation to collect information from each IoT system. In the specific application, information obtained from IoT devices reveals a covering challenge [28]. The positioning of the drones has an impact on the connection link between the drone and the IoT devices within a specific application, and the connectedness has an impact on system performance. Drone movement patterns are thus an important piece of technology for enhancing network connections and coverage within approaches [29]. The angular, tractor, circular, and square movement patterns have been identified. In analyzing connection speeds, the tradeoff between flying drone patterns and processing times must be taken into account. By reducing the total of unavailable devices connected to the network, the drone’s movement pattern could increase the coverage. As a result, better drone movement could be obtained if an appropriate place is determined, which is one of the goals of the work. Because of the drones’ low - power consumption, they must conduct movement and communications efficiently. As a result, drones must autonomously alter their locations to achieve the desired connection speed for IoT systems while conserving energy. It links to the BS having strong signal strength using a deep learning algorithm that reduces the number of handoffs with such a modest degradation of signal strength. Movement maintenance, on the other hand, is not taken into account since it does not handle BS, numerous drones, or phone devices. The drones could receive data from IoT devices and cover various possible applications from such a fixed-known route to regulate the drone altitude. Drone movement and position could be modified, allowing the drone to advance toward that IoT framework and obtain sustainable power conservation when connecting [30]. The major goal is to assist effective drone movement by ensuring the good QoS performance of IoT systems in the framework and increasing the signal strength of the drones.

\[ md_A = d_10 \left[ ss_r [d_r] - ss_r [md_A] \right] \times 10^b, \quad (5) \]

here \( ss_r \) is at a reference distance of \( d_r \). \( md_A \) denotes the actual distance in between drones’ location and the IoT devices, and it is the path coefficient. The ideal height \( h^b \) for the drones ranges from \( \text{min}_h \) to \( \text{max}_h \), as shown in the following:

\[ O^h = a_{h; \text{min}_h, \text{max}_h} \min \left[ \sum_{t=1}^{T} \left[ d_{it} - h^b - r^2 \right] \right], \quad (6) \]

here \( d_{it} \) is the distances between the drones at positions \( (An; Bn) \) on trajectories \( T \) and the standard IoT device \( (An; Bn) \) in the approaches, as determined by signal strength. The distance between the drone and \( L \) IoT devices at trajectories location \( (An; Bn) \) is provided as follows:

\[ r = \sqrt{d_{\text{max}}^2 + O^h^2}, \quad (7) \]

\( d_{\text{max}} \) is the distance between the drones location at \( T \) trajectories point \( (An; Bn) \) and the IoT devices in the application region.

The received signal intensity is dynamically upgraded with different drone positions, and ANN is used to forecast drone movement. The illustrations of drones flying at different ranges are shown in Figure 7. The ideal transmission range of the drones from various heights could be predicted.
in this scenario of predicting signal strength at various positions.

3. Proposed Methodology

Drones are flying electronics that fly through the air. It really has sparked a strong interest for usage in various situations. Drones are important in wireless transmission in a variety of transitory situations, including disasters, transportation, sales, emergency surveillance, vehicle tracking, and athletics. As a result, drones could indeed intelligently carry out tasks in a variety of fields to benefit society, market, and administration, such as greater resolution picture quality, lower costs, faster response, the ability to fly in almost any situation, the ability to be nearer to areas of monotonous study, and for use in dangerous activities. The signal strength must be estimated to use an accurate approach to enhance transmitting and receiving architecture. An ANN is presented for anticipating the precise signal from various altitudes and distances.

$$b_{p1}(n) = \left[ b_p(n) \ldots b_{p20}(n) \right].$$ \hspace{1cm} (8)

All that should be initialized in equation is as follows: (8) the center value $c_{x}(0)$, the span value $s_{x}sv(0)$, the weight vector $b_{p}(0)$, and the expectation $b11(0) = b21(0)$.

The formulas used to calculate the hidden layer output, output, and error in equations (9) and (10) are as follows:

$$S_p = r \left[ \sum_{k=1}^{L} b_{py(n)A_x} \right], \quad p = 1, 2; L = 20.$$ \hspace{1cm} (9)

$$u_p = d_p - S_p,$$ \hspace{1cm} (10)

Here $d_p \in [0, 1]$ is the required layout, and the weights are updated as follows 11:

$$b_{py}(n + 1) = b_{py}(n) - \alpha_b A_{x}. $$ \hspace{1cm} (11)

Update the center and span momentum, where $\alpha_b$ indicates the weight and $\alpha_c$ indicates the centre learning rates, respectively, in equations (12) and (13).

$$cv_{xy}(n + 1) = cv_{xy}(n) + \alpha_c \frac{A_{x}}{sv} (a_x - cv_{xy}(n)) \sum u_p b_{py}(n).$$ \hspace{1cm} (12)

$$sv(n + 1) = sv(n) - \frac{2\alpha_c A_{x}}{sv(n)} \ln A_{y} \sum u_p b_{py}(n).$$ \hspace{1cm} (13)

The data needed to create an appreciative drone communications system will be processed by ANN. The goal of the ANN approach is to quickly and successfully manage the link between drones, IoT devices, grounded robotics, and users. ANN is made of a number of neurons that are organized in a specific way, as seen in Figure 8. Distance ($d_i$), height ($a_h$), frequencies ($f_r$), and path loss are among the inputs ($l_p$). The buried layer’s total is equal to the outputs. The outputs determine and evaluates the signal strength appreciation (S).

The input layer only serves as an entrance point for the input signal. It does not do any analysis. The hidden layer is composed of many Gaussian functions that act as random finite elements, allowing the input sequence to be expanded over the hidden layer region. It is a nonlinear transition from the input vector to the hidden state region. The output layer produces an output sequence by linearly combining the hidden layer outputs.

The following is how the ANN learning method operates: mostly on terminals linking the input layer and the hidden layer, the neural network is initialized with appropriate initialization. The initial set of input variables is then sent to the ANN. It processes the data and provides an outcome. Backpropagation is used to transmit the error between the generated output and the support vectors backwards further into system, and the weights are changed to reduce the error. The function is conducted repeatedly for every one of the training instances, and the final weights are saved as a guideline for sustainable forecasts on unknown data. The MSE, RMSE, and coefficient determination (R2) parameters are common error measurements for neural network learning tasks. It should be noted that such a method of utilizing the ANN for prediction problems linked to wireless communication technology was already demonstrated to be successful. In a prior study, the findings indicated that utilizing ANN to forecast transfer between the earthly communications network and HAP had been the most effective method for making an appropriate choice regarding RSS. The data based on the Hata parameter estimation are generated for the training and evaluation of the proposed ANN model enabling signal strength forecasting. The metrics of distance, frequency, path loss (PL), and RSS and spaces are calculated, which are presented as inputs to the ANN throughout training and
validation. Following ANN’s output of a signal strength rating depending on the input model parameters, that value is then compared with the RSS frequency for determining error metrics and weight modification utilizing back-propagation techniques.

The whole ANN training, calibrating, verification, and installation work-flow, as well as the necessary data pre-processing stages, are depicted in Figure 9. In the first phase, the proposed method is initialized and information is preprocessed, after which all variables are combined. The ANN network is adjusted for the set of input layer neurons, hidden unit nodes, and training algorithm, and standard weighting are initialized. ANN is trained in the calibrating phase by analyzing the input variables and intended output (signal strength). The method is considered the final model once error parameters are minimized. The mean square error (MSE), root means square error (RMSE), and coefficient determination (R2) measures are used in the evaluation of training models.

3.1. Evaluation of Performance. The trained ANN model on the generated dataset and measuring the inaccuracy in the estimates provided an early evaluation of the suggested technique’s effectiveness. The three main parameters had been used to calculate the standard errors: MSE, RMSE, and R2. MSE stands for mean square error, and a number around 0 indicates a high-performing algorithm equation (14). The root-mean-square error (RMSE) is defined as the square root of the sample mean instant of the distinctions among simulated and experimental numbers, or the quadratic mean among those variations, with numbers near zero indicating a viable system equation (15). The determination coefficient (R2) is a measurable statistic of the data’s resemblance to the linear regression line. The R2 score ranges from 0 to 1, with 0 indicating that such analysis includes minimal variance in the data and 1 indicating that its prediction is flawless. R2 values that are nearer to zero are clearly preferable to equation (16).

\[
\text{Means square Error} = \frac{1}{n} \sum_{x=1}^{n} (B_x - A_x)^2, \quad (14)
\]

\[
\text{Root Mean squared error} = \sqrt{\frac{1}{n} \sum_{x=1}^{n} (B_x - A_x)^2}, \quad (15)
\]

\[
\text{Regression metrics} = 1 - \frac{\sum_{x=1}^{n} (B_x - (1/n)\sum_{x=1}^{n} A_x)^2}{\sum_{x=1}^{n} (B_x - A_x)^2}, \quad (16)
\]

After the model’s primary measuring performance on gathered information, it must have been assessed once more with noisy data applied to the entire data. It was performed to verify that the theory was strong enough to be used in specific circumstances.

4. Result and Discussion

The effectiveness of the suggested ANN approach for signal strength forecasting is evaluated throughout this article. The algorithm has been trained and finished according to the flowchart, and it is being used to make RSS estimations. Because many real-world data that would be fed into the algorithm following implementation would have been unclear, it was thought necessary to assess the model’s stability in the presence of imbalanced datasets. The author starts with a collection of IoT systems in well-known possible applications in a smart city and then assumes that such a drone will be in a specific spot to the application region’s IoT systems. The drone’s flight speed is ignored as well as the time it takes to get there in this situation. The suggested ANN could accurately forecast signal strength, including all IoT systems in various areas and altitudes from the drones with minimal computing performance, according to the findings. The ANN is trained for 100 rounds offline. The suggested method’s assessment measures MSE, RMSE, and R are computed. In the other instance, a collection of IoT gadgets is attached to a drone, which moves through a series of places. The MSE, RMSE, and R evaluation metrics are calculated for the suggested approach once more. When drones are put at a high elevation, they can accommodate a greater number of IoT devices, however, every IoT system must use more capabilities to achieve adequate signal strength for communications with the drones. As a result, it is essentially a tradeoff between the variety of devices a drones could operate and the energy requirements of specific IoT devices. If the drone’s location is specified, it is simple to calculate how many IoT system may be used to receive the signal strength throughout this circumstance. For information collection through IoT devices, ANN is used to anticipate drone movements in trajectories based on signal strength based on movement drones. Based on the prior signal strength, the next point in the path could be anticipated. As a result, the following IoT devices inside the drone’s path could be prepared to relay collected information to the drone whenever the drone is within the range.
of the device. As a result, every IoT system would save a considerable amount of energy by not having to keep its wireless connection on most of the times.

For the training and testing sets, the analytical measures of MSE, RMSE, and R2 are performed to analyze the strongest ANN technique for estimating signal intensity distribution compared to the input variables. The outcomes of the suggested ANN method are shown in Table 1. They include various error measurement numbers. In terms of ANN predictive performance, the R2 values of 0.97 and 0.98 were obtained in the case of various height and distance circumstances, correspondingly. Figure 10 depicts the graphical representation on ANN metrics. In numerous scenarios, the total R2 values reveal that such levels are significant enough to enable highly accurate results of the ideal signal traveling from the drones to a gadget in smart city environments. The projected quantities have also been evaluated with their ground-truth equivalents, yielding a median percentage of error of 1.10% across all projections. Finally, the amount of time required for the system to generate one prediction was assessed, and the algorithm was capable of doing it in 11 milliseconds. Such a prediction speed was determined on a desktop computer with average specs, and hardware implementations will undoubtedly be much quicker.

When the drone has been regarded stable at various distances, ANN estimated the signal strength from the drone once again. The drone was placed in a particular place, sample was gathered for various ranges to the IoT device, and then an artificial neural network (ANN) was used to forecast the connection depending on signal strength at various distances. The ANN projections for signal strength were found to agree with the observed data output. Moreover, uncertainty was applied to the input data, and assessments are performed to determine the reliability of the suggested ANN for implementation in real-world applications. The signal strength forecast is caused by the movement of drones at various heights across ground-based IoT systems. The effectiveness of the ANN model was assessed using the assessment measures MSE, RMSE, and R2. The maximum level of the regression model (R2 = 0.98) indicates that the proposed approach has a greater accuracy. Real-time drone trajectory adjustments help to improve connection reliability and deliver higher QoS for the drone network coverage. The flying-path is found to alter in response to the signal strength. ANN accurately predicts the drone’s position for a particular signal strength parameter, and it could also anticipate the next position derived from the previous one. As a result, the ability to forecast drone flight paths and identify drone network coverage can help meet the need to sustain performance.

While it may seem that including the path loss in the learning algorithm for the suggested ANN is unnecessary because all of the parameters around which it is reliant are indeed taken into account as independent features in the training phase, it was meant to give the ANN layout for such an implementation to the succeeding flexibility. In this

| Method        | Mean squared error | Root-MSE | Regression |
|---------------|--------------------|----------|------------|
| Various altitude | 13.52              | 2.68     | 0.97       |
| Various length     | 1.72               | 1.24     | 0.98       |

Figure 10: Graphical representation of ANN measurements.
scenario, the numbers are actually influenced by certain factors, such as $d_i$ and $f_r$. It might not be the case for many other path loss approaches, which could be reliant on variables that were not included in the ANN model. It is especially relevant for nondeterministic systems. With the current growth in research efforts to achieve the highest accuracy machine learning algorithm for route loss, the paper’s suggested technique is more relevant.

5. Conclusion

Artificial intelligence (AI) combined with the connectivity of drones and the Internet of Things (IoT) may there be major interaction and complicated solutions to today’s issues.

(i) As a result, it is seen as a miniature of IoT, and it is already starting to effectively replace linked devices at fixed locations. IoT devices are not capable of sending information across great distances. Furthermore, combining drones and IoT devices would provide a resolution to today’s issues.

(ii) Fast (real-time) and accurate calculation of the RSS from the drones at the base stations is required for effectively operating drones beyond a wide geographical region with a multitude of nodes. The signal strength is forecasted efficiently and accurately depending on height, loss rate, and distance utilizing ANN.

(iii) The use of artificial neural networks (ANNs) is critical in the training of large amounts of data in a short amount of time. It also makes accurate predictions and recognizes decisions. The MSE, RMSE, and R-squared measurements were used to assess the suggested technique’s effectiveness.

(iv) At a variety of heights and distances, the ANN-based signal strength method produces accurate forecasts with RMSE values of 2.68 percent and 1.24 percent, respectively. The acquired results demonstrated that the suggested ANN may be used in a real-world IoT scenario to predict an RSS from a drone.

Data Availability

The data used to support the findings of this study are included within the article. Further data or information is available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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