J. Electrical Systems 20-7s (2024): 2923-2938

Yawei Duan[1*]

Application of UAV Technology in Smart Construction in Construction Monitoring

Abstract: - The unmanned aerial vehicles (UAVs), construction sites may obtain detailed aerial imagery and used to create 3D models and track development in real time. UAVs capture aerial data, enabling creation of 3D models and real-time progress tracking. This improves both safety by allowing inspections of risky areas and efficiency by offering a comprehensive view of the entire site. In this research application of UAV technology in smart construction in construction monitoring is proposed. Initially, the images are collected from Drone-View Building Identification by Cross-View Visual Learning and Relative Spatial Estimation (DVBI-CVVL-RSE) dataset. Then, the collected data is fed to Pre-processing segment. In pre-processing stage, Unscented Trainable Kalman Filter (UTKF) used to remove the noise. Then pre-processed output is given to Multi-Objective Matched Synchrosqueezing Chirplet Transform (MOMSCT) is used to extracting the image features such as shape, colour, and texture. The extracting features are fed into the pseudo-hamiltonian neural networks (PHNN) used to forecast the class and location of construction building site in a full image or video. The UAV is using to capture the photo of construction site and Used to track in construction site work progress in real time. The weight parameters of MORARNN are optimized using Osprey Optimization Algorithm (OOA).Therefore, the suggested approach looked at using performance measures like accuracy, computation time, error rate, Fl-score, precision, recall, receiver operating characteristic curve (ROC), Sensitivity and specificity. The proposed PJH-CPI-CS-RBNN approach attains29%, 24.5% and 20% higher accuracy, 30%, 20% and 25.5% higher Precision and 27.5%, 25.5% and 22% higher sensitivity compared with existing methods such as Towards UAVs in construction: advancements, challenges, future directions for monitoring (VAVC-ACFDMT-RNN), Change detection in unmanned aerial vehicle imageries for progress monitoring of road construction (CD-UAVT-PMRC-ANN), and Application of deep learning with unmanned aerial vehicle on building maintenance (ADL-UAV-BM-CNN).By comparing other three existing methods, the proposed PJH-CPI-CS-RBNN method gives high accuracy models respectively.

Keywords: Construction, Unmanned Aerial Vehicle (UAV), Technology, Weight, Time Consuming, Expensive, sensor and Error.

I. INTRODUCTION

(a) Background

The construction industry has traditionally relied on manual methods for tasks like surveying, inspection, and progress monitoring [1, 2]. Particularly for large or complex projects, these methods can be costly, time-consuming, and even deadly [3, 4]. UAVs or drones have become a game changer in this field [5, 6]. They are perfect for a range of construction applications because of their capacity to maneuver through challenging terrain [7], collect high-resolution data, and access confined spaces [8]. Efficiency, safety, and cost-effectiveness have all significantly increased as a consequence [9], all throughout the construction lifespan [10].

(b) Literature Review

Various research works have previously existed in the literature which was based on application of UAV technology in smart construction in construction monitoring. Some of them reviewed were follows,

Liang et al. [11] have introduced recent advancements in the use of unmanned aerial vehicles for monitoring and inspection in the construction sector, as well as an investigation of the various drone and sensor types used and their uses. It emphasizes how far technology has come in this area. Like with any new technology, there were, however, issues and constraints to be resolved. These include issues with safety, technological constraints, data processing, legal and regulatory issues, and training and competence. Here are some potential directions for further study and an overview of the advantages of drone-based construction inspection. These comprise the use of artificial intelligence (AI) and machine learning for data analysis, integration with other construction technologies, and innovative sensors and imaging technologies.

Han et al. [12] have introduced a technique that employs deep learning and several temporal photos to automatically identify the construction area. First, reference photos of the changing area were used to build a deep learning model. Second, by adjusting several deep learning process parameters, were able to derive an efficient application technique. When the time-series photographs of a construction site were applied to the selected deep learning model, it was possible to identify the altered sites with greater accuracy than with the

[1] [1*]School of civil engineering and architecture, Zhengzhou university of aeronautics, Zhengzhou, Henan, 450046, China

[1*]Email: profyaweiduan@gmail.com

previous pixel-based change detection method. By promoting the advancement of intelligent construction technology, the suggested approach was anticipated to be highly beneficial for construction management.

Kung et al. [13] have introduced an automated image-based approach using convolutional neural networks (CNNs) to detect and locate critical building flaws (efflorescence, spalling, cracking, and defacement). This model uses class activation mapping for object localization and was based on a pretrained CNN VGG-16 classifier. This study assessed the resilience and precision with which the model could identify and localize flaws in building exterior wall tiles, as well as its limitations in practical applications. This study implemented this model using drones and mobile devices for real-time detection and localization.

Mahajan [14] has introduced the construction industry's potential of DT, expanding it to better grasp the following concerns(i) Describe the advantages and effects of drones in CI; (ii) List the drawbacks of drones in CI(iii) large length and volume integration of BIM with DT (iv) thorough explanation and listing of the functions and applications of drones in CI(v) using drones at every step of construction to track development accurately from the time land was purchased until the project was completed (vi)A comment regarding the effect of COVID-19 on construction was finally inserted. The obstacles, chances, restrictions, and tactics for the use of drones in construction were also covered in this study (2012–2021). It helps academics, building planners, designers, engineers, architects, contractors, and builders enhance construction operations for increased effectiveness and superior. It encourages the addition of these technologies to the Architecture Engineering program as well.

Namian et al. [15] have introduced a One of the riskiest sectors of the US economy was construction. Apart from the typical risks associated with dynamic construction environments, Workers may be exposed to a wider range of safety issues by using UAVs, which means they must be recognized and addressed. Due to a lack of knowledge on the risks and hazards associated with drone use, the industry does not have the safety protocols necessary to prevent any accidents. The purpose was to: (1) identify the construction-related UAV-associated dangers that could endanger people or property; (2) evaluate the relative importance of every hazard and related safety risks. Phase I comprised the investigators conducting a comprehensive examination and consulting with a building-related UAV professional. In Phase II, data from 54 construction specialists were gathered by the researchers, who used it to validate and assess the risks and hazards that had been discovered.

Hatouma and Nassereddineb[16] have introduced an Industry 4.0 may be the bright spot for the construction sector, which has been dealing with difficult, long-term issues for many years. Live in a turbulent, uncertain, complex, and ambiguous world. The well-documented revolutionary influence of Industry 4.0 has piqued the interest of construction researchers in investigating the potential benefits that this industry may offer. Drones, one of the many technologies introduced by Industry 4.0, have become increasingly common in the construction sector. This study highlights the present status of drone adoption in the construction industry, building on the body of existing knowledge. In order to meet the research goal, the several uses of drones in building projects were investigated, cost, benefit, and difficulty factors were noted, and important factors were talked about. Thesummary of the "5W2H" factors, which include the Who, How Much, When, Where, Why, and what kinds of drones were used in the construction sector.

York et al. [17] have introduced an in-depth analysis that identifies the barriers to the wider application of unmanned aerial vehicles (UAVs) in the construction industry as well as their potential applications. Applications that reduce material waste, speed up inspections, lower surveying costs, and improve workplace safety were given. The outcomes show that the current problems can be broadly classified as 3 main areas: (1) legal with regulatory requirements; (2) unmanned aerial vehicle characteristics and functionalities; and (3) software attributes and functionalities for data collection, processing, and display. However, this study will not discuss issues about the features and abilities of data gathering and processing owing to various software available and the disparity in claimed accuracy.

(c) Research Gap and Motivation

Even though construction monitoring has been completely transformed by UAVs (unmanned aerial vehicles), there are still unanswered research questions [18]. Increasing automation and data analysis is one important area [19]. As of right now, processing drone data to create 3D models and spot plan deviations can be labor-intensive and require human skill [20]. Research is required to create autonomous analysis tools that can effectively manage this task, enabling quicker decision-making and real-time progress tracking [21]. Integrating UAV data with Building Information Modeling (BIM) is another area of weakness. A digital representation of the whole building project is produced via BIM [22]. Enhancing predictability of the project and facilitating proactive adjustments would be possible. Addressing these gaps is motivated by important factors. Increased productivity, lower costs, and better project outcomes are what smart construction will achieve with enhanced automation and BIM integration [23]. UAVs can also significantly improve safety by lowering the need for workers to enter dangerous areas and enabling remote inspections of those areas. With additional investigation, UAV technology could completely change construction monitoring inside the framework of smart construction [24].

(d) Challenge

While UAVs (Unmanned Aerial Vehicles) or drones offer a powerful toolset for smart construction monitoring, there are challenges to consider [25]. Here's a breakdown of some key hurdles. Wind, rain, and low visibility can significantly impact drone operation. Construction projects often face delays due to unfavourable weather conditions [26]. Drones equipped with high-resolution cameras capture sensitive data. Ensuring proper data storage, security protocols, and respecting privacy regulations is crucial. Balancing flight time with the weight of sensors and cameras can be tricky. Drones with heavier payloads may have shorter flight durations, requiring more frequent battery changes [27]. Effectively integrating UAV data into existing construction management workflows requires proper training and data processing software.

(e) Contribution

- The major contribution of this work is to propose application of UAV technology in smart construction in construction monitoring using OOA-PHNN approach.
- The proposed method is the joint operation of Osprey Optimization Algorithm(OOA) and Pseudo-Hamiltonian Neural Networks (PHNN).
- The proposed method is implemented in the MATLAB.
- The proposed method shows the better results compared with other existing methods.

(f) Organization

Section 1 describe the introduction is explain the literature review and background of the research work, Section 2 includes the proposed methodology, Section 3 includes the results and discussion, Section 4 clarifies the Conclusion and Section 4 the manuscript concludes.

II. PROPOSED METHODOLOGY

In this section application of UAV technology in smart construction in construction monitoring using OOA-PHNN approach. Block diagram of proposed AUAVT-SC-CM-OOA-PHNN is presented in Fig 1. It comprises dataset preparation, pre-processing, feature selection, optimization. The description of all stages depicted below,

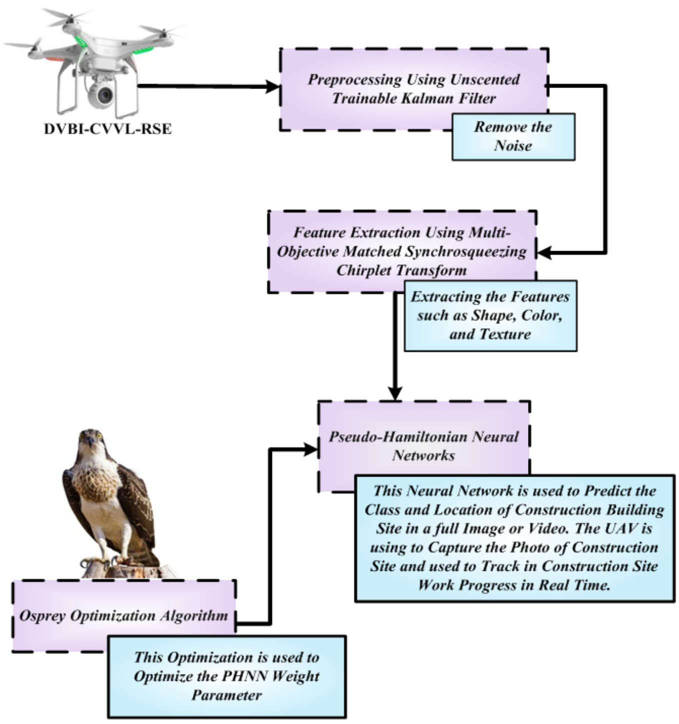

Fig 1: Proposed AUAVT-SC-CM-OOA-PHNN method

A. DataAcquisition

DVBI-CVVL-RSE of UAV technology in smart construction are used in this study [28]. Recently, drones have gained popularity and are equipped with more sensors than regular cameras, opening up new research and applications. Providing relevant information (such as a building) to comprehend the drone's surroundings is crucial for enabling drone-based applications. Our goal is to identify the most likely suggestion (building candidate) on a drone-view image given a building (multimodal query) that includes its photos, geolocation, and the drone's present location. This is how we frame the challenge of drone-view building identification: building retrieval. Although there aren't many annotated drone-view photos yet, there are plenty of other perspectives available on the Internet, such as aerial, street-view, and ground-level photos. Therefore, in order to learn visual similarity between drone-view and other views, we further develop relative spatial estimation of each proposal and the drone, and we gather new drone-view datasets for the task using a cross-view triplet neural network. This method outperforms triplet neural network by 0.12 mAP.

B. Pre- Processing Using Unscented Trainable Kalman Filter

In this section Unscented Trainable Kalman Filter (UTKF) [29] technique is used. The advantage of the Unscented Kalman Filters (UKFs) with UAV technology in construction monitoring is its ability to handle non-linearities in sensor. In contrast to conventional Kalman Filters, UKFs are capable of handling scenarios in which there is a non-linear relationship between the data taken by the UAV and the real conditions of the construction site UTKF technique is used to remove the noise. This is especially important in construction contexts, where sensor data anomalies can be caused by partially completed structures or uneven terrain. UKFs offer more precise and trustworthy estimations of the parameters of building sites by taking these non-linearities into account, which improves decision-making and project monitoring all along the way. Projecting future circumstances or impacts using known data and historical trends is the process of prediction. Then the prediction process is defined as equation (1),

$$v^I = s(G^I D) + q^I \tag{1}$$

Here v^I specifies output of the prediction process; s denotes the activation function; G^I denotes the weighed matrix; D denotes the input data and q^I denotes the constant term. A prediction state is a condition or outcome that is estimated or anticipated based on available data and long-term patterns. It is defined as the following eqn (2),

$$\hat{v}(t+1) = f(D(t)) \tag{2}$$

Herein $\hat{v}(t+1)$ denotes prediction state and $f(D(t))$ denotes the function of output data. A residual function computes the difference between the actual outcome and the expected outcome generated by a model or algorithm. It is frequently used in machine learning and optimization techniques. This difference indicates regions where the model's predictions need to be adjusted, which helps assess the model's accuracy. The residual function defined as eqn (3),

$$\in(t+1) = s(v(t+1), \hat{v}(t+1)) \tag{3}$$

Consider $\in(t+1)$ denotes residual at time $t+1$; s denotes the residual function; $\hat{v}(t+1)$ denotes the prediction state and $v(t+1)$ denotes the state at time $t+1$. If the state matrix contains the data, to estimation process would be disrupted because the estimator cannot compute the difference between the predicted state and the actual state. This absence impedes the calculation of deviations, which are essential for accurate estimation. It is defined as the following eqn (4),

$$\hat{v}(t+1) = f(D_{1:t}(t)) \tag{4}$$

Let $\hat{v}(t+1)$ denotes the prediction state and $f(D_{1:t}(t))$ denotes state time-series matrix from initial time to time t. The most accurate representation of a method's current state or variables is referred to as the optimal estimation state; this representation is usually obtained using mathematical techniques in order to minimize error. The most accurate state estimate in a Kalman filter is ensured by applying a weight factor, known as the optimal Kalman gain, to the difference between anticipated and observed data. The optimal Kalman gain is defined as eqn (5),

$$K = \hat{\Sigma}_{vx}(t+1)[\hat{\Sigma}_{x}(t+1))]^{-1} \quad (5)$$

Where, K denotes the Kalman gain; $\hat{\Sigma}_{vx}(t+1)$ denotes the covariance matrix and $\hat{\Sigma}_{x}(t+1)$ denotes the covariance matrix of Kalman gain. By processing UTKF method remove the outlier from the input data from the collected dataset. Then, the pre-processed data are fed to feature extraction phase.

C. Feature Extraction using Multi-Objective Matched Synchrosqueezing Chirplet Transform

In this step, feature extraction using MOMSCT is discussed [29]. To extract features from the segmented output, including shape, color, and texture, MOMSCT is used. A multi-component signal $S(T)$ having characteristics, and then formulate it as:

$$S(T) = \sum_{k=1}^{K} A_k(T) E^{I_{\varphi k(T)}} \quad (6)$$

Here K as total signal components, $A_k(T)$ and $\varphi k(T)$ as k component's instantaneous amplitude (IA) and instantaneous phase (IP). The signal is subjected to STFT. The shape $G(U)$ eqn (7):

$$G(U) = \int_{-\infty}^{+\infty} S(U) g(U-T) E^{-I\omega(U-T)} DU \quad (7)$$

When a signal exhibits significant time variation, a higher-order Taylor expansion must be used to characterize the signal's phase function. Consider $\exists\varepsilon$ is small, for $\forall T, \left|\varphi_k^{'''}(T)\right| \le \varepsilon$, and $A_k^{'}(T) \le \varepsilon$. A second-order expansion of the signal is written as the form $U = T$, $A_k(U) = A_k(T)$. The color ($\varphi_k(U)$ and texture ($S(U)$) is labelled in [8-9] :

$$\varphi_k(U) = \varphi_k(T) + \varphi_k^{'}(U)(U-T) + \frac{\varphi_k^{'''}(U)(U-T)^2}{2} \quad (8)$$

$$S(U) = \sum_{k=1}^{K} A_k(T) E^{I\left[\varphi_k(T) + \varphi_k^{'}(U-T) + \frac{\varphi_k^{'''}(T)(U-T)^2}{2}\right]} \quad (9)$$

Wherein $\varphi_k^{'}(U)$ and $\varphi_k^{'''}(U)$ signifies instantaneous frequency as well as modulation rate of k component of the signal. The optimal frequency interval $\Delta_\omega(T)$ in LMSST is shown in (10).

$$\Delta_\omega(T) = \sum_{k=1}^{K} \sqrt{2[1+\varphi_k^{''}(T)^2]\, In \frac{1}{T_0}} \quad (10)$$

Here $\Delta_\omega(T)$ value is determined by window function width T_0 and modulation rate $\varphi_k^{''}(T)$. However, it is challenging to determine the modulation rate directly for the majority of signals. Therefore, it is equally challenging to compute the ideal frequency interval value.Finally, Multi-Objective MOMSCT has extracted the features such as shape, color, and texture. After completing the feature extraction, the extracted features are fed to Pseudo-Hamiltonian Neural Networks (PHNN).

D. Pseudo-Hamiltonian Neural Networks (PHNN)

Studying dynamical systems that are characterized by ordinary differential equations is made possible by the use of PHNNs, a unique method. This neural network is used to forecast the class as well as positioning construction building site in a full picture or video. The UAV is using to capture the photo of construction site and used to track in construction site work progress in real time. The features within the ultrasound pictures can be captured using PHNN models. They present numerical proof of PHNN's superior performance comparing with baseline mode that simulates the whole dynamics with single neural network [30]. To further gain a deeper knowledge of the system, each of the three PHNN model components each with a unique physical interpretation can be studied separately. In the case that external influences are removed or altered, the learned model might still be utilized. These systems possess the ability to learn about what are known as Pseudo Hamiltonian Systems, which expand the meaning of Hamiltonian systems to include any system that preserves invariants while also taking dissipation and external influences into consideration.

$$X = (S(X) - R(X))\nabla H(X) + F(X,T), \qquad X \in R^d \tag{11}$$

For every y, here are $S(X) = -S(X)^t$ and $y^t R(X) y \geq 0$. That is, $(x) \in \mathbb{R} d \times d$as any positive semi-definite matrix, and $S(X) \in R^{d \times d}$ can be any skew-symmetric matrix. In theory can obtain a pseudo Hamiltonian formulation for any first-order ODE by putting no limits on the external forces. This can then be acquired by a variable transformation from any arbitrary-order ODE. With this formulation, models are divided as internal dynamics and external forces can be learned. It is $\hat{F}_\theta(X,T)$ and $(\hat{S}_\theta(X) - \hat{R}_\theta(X))\nabla \hat{H}_\theta(X)$.This limits the model's capacity to handle systems that are less generic in some aspects, since it requires a certain level of uniqueness in this division. One of the many significant benefits of this component of the PHNN approach is its ability to train a system model as though it were operating in perfect conditions even when the input comes from a system that encounters disturbances. The class of PDEs ξ that can be expressed in a certain way will be covered in this essay.

$$\xi = S(U^A, X)\frac{\partial H}{\partial U}[U] - R(U^A, X)\frac{\partial V}{\partial U}[U] + F(U^A, X, T) \tag{12}$$

When H and V are integrals of the form $F : R \times R^d \times R \to R$ an $S(U^A, X)$ and $R(U^A, X)$ are operators that have the characteristics of being positive semi-definite in terms of inner product along skew symmetric. This class of pseudo Hamiltonian PDEs is worth noting, as it aligns with our previous research and highlights the link to the extensive body of literature on Hamiltonian neural networks. Furthermore, this expansion encompasses infinite dimensional systems and presents a broader definition that allows for the consideration of two distinct integrals, H and V. With the exception of a certain term F ,which are a smart fusion of symplectic and metric functions. If ignore the term F, may call this class of PDEs metriplectic PDEs, a combination of "metric" and "symplectic." metriplectic PDEs include Burgers and Navier-Stokes equation. With the exception of F and $R(U^A, X)$, the formulation is same as infinite-dimensional variation due to its positive nature rather than its negative semi-definiteness of the GENERIC formalism from thermodynamics. In addition, the degeneracy conditions are necessary according to the GENERIC formalism.

$$R(U^A, X)\frac{\partial H}{\partial U}[U] = S(U^A, X)\frac{\partial V}{\partial U}[U] = 0 \tag{13}$$

The equation needs to be met. They do not put this requirement on our model because do not believe it to be satisfied. Study has been done on neural networks that preserve the finite-dimensional instance of the GENERIC formalism. Given that u is periodic, the discretization of the operators, S, and R will inevitably produce circulating matrices as Let's assume that they are independent of x and u. As an energy policy analyst In other words, they can be compared to discrete convolution operators. Given the indications of K_1, K_2 and K_3, $\hat{A}_\theta^{K_2}$, $\hat{S}_\theta^{K_2}$ and $\hat{R}_\theta^{K_3}$ regarding kernel sizes, they have decided to make the trainable convolution operators. Also enforce symmetry on $\hat{A}_\theta^{K_2}$ and skew symmetry on $\hat{S}_\theta^{K_2}$ through $\hat{R}_\theta^{K_3}$. In addition, $\hat{V}_\theta$ and $\hat{H}_\theta$ are two separate neural networks that produce a single value and consider input vectors with length M, which stands for the quantity of discretized spatial points. The complete model for PDEs is then provided by the pseudo-Hamiltonian neural network. When give input vectors for the U, X and T the neural network $\hat{F}_\theta$ can produce a vector with length M.Then, the complete PDE neural network model for pseudo-Hamiltonian systems is provided.

$$\hat{G}_\theta(U,X,T) = (\hat{A}_\theta^{K_1})^{-1}\left(\hat{S}_\theta^{K_2} \nabla \hat{H}_\theta(U) - \hat{R}_\theta^{K_3} \nabla \hat{V}_\theta(U) + K_4 \hat{f}_\theta(U,X,T)\right) \tag{14}$$

Additionally, k_4 has been included. Its value should be either 1 or 0, indicating our desire to successfully estimate the class and place of construction building site in a full image or video. The UAV is using to capture the photo of construction site and used to track in construction site work progress in real time..

E. Osprey Optimization Algorithm (OOA)

The Osprey Optimization Algorithm (OOA) is a novel metaheuristic algorithm that mimics osprey behavior in the wild [31]. PHNN weight parameter ξ is optimized by OOA. The primary source of inspiration for OOA is the tactic used by ospreys to catch fish in the ocean. Using this hunting tactic, the osprey locates its prey, hunts it, and then transports it to a good eating location. Depend on simulation of ospreys' natural behavior when hunting, a mathematical model of OOA's two-phase exploration and exploitation strategy has been developed.

Step 1: Initialization

The OOA is a population-based method that can produce a suitable answer based on the capacity of its population members to explore the problem-solving space through a repetition-based procedure. As individuals within the OOA population, each osprey establishes values for the problem variables according to where it is located within the search space. Thus, Each osprey is a mathematical representation of a possible resolution to the problem, using a vector. All ospreys comprise the OOA population, which can be represented using a matrix in accordance with (15). When the OOA implementation begins, (16) is used to randomly identify the starting position of ospreys in the search space.

$$Q=\begin{bmatrix} Q_1 \\ \vdots \\ Q_I \\ \vdots \\ Q_N \end{bmatrix}_{N\times M} = \begin{bmatrix} q_{1,1} & \cdots & q_{1,J} & \cdots & q_{1,M} \\ \vdots & \ddots & \vdots & \iddots & \vdots \\ q_{I,1} & \cdots & q_{I,J} & \cdots & q_{I,M} \\ \vdots & \iddots & \vdots & \ddots & \vdots \\ q_{N,1} & \cdots & q_{N,J} & \cdots & q_{N,M} \end{bmatrix}_{N\times M} \tag{15}$$

$$q_{I,J} = 1b_J + r_{I,J}\,.(ub_J - lb_J),\quad I = 1,2,\ldots\ldots,\ N,\quad J = 1,2,\ldots\ldots,\ M \tag{16}$$

Where Q denotes population matrix of ospreys' locations, Q_1 exhibits I osprey, $q_{I,J}$ express J dimension (problem variable), N as number of ospreys, m as count of problem variables, $r_{I,J}$ specifies random count at [0, 1], lb_J , and ub_J specifies lower bound and upper bound of the J problem variable.

Step 2: Random Generation

After initialization, weight parameters are formed randomwise.

Step 3: Fitness Function

To calculate the fitness value utilizing

$$Fitness\ Function = MIN(\xi) \tag{17}$$

Step 4: Position identification and hunting the fish (exploration)

Ospreys are powerful hunters that can find fish underwater because to their acute vision. When they've found the fish, they attack it and go under to pursue the fish. Phase I of the OOA population update is modeled using a simulation of osprey behavior in the wild. When the osprey attack is represented, the position of the osprey in the search space is considerably changed, increasing OOA's exploration capacity in locating the optimal site and avoiding local optima. Underwater fish are identified in the OOA design as other osprey placements in the search area with a greater objective function value for each osprey. A set of fish for every osprey is specified in eqn (18),

$$FP_I = \{Q_K \mid K \in \{1,2,3,\ldots,N\} \wedge F_K < F_I\} \cup \{Q_{BEST}\} \tag{18}$$

Here FP_I specifies set of fish locations for i osprey, Q_{BEST} is the best candidate solution. One of these fish is randomly located by the osprey, which then strikes it.A new location for the matching osprey is determined using (19–20) based on the simulation of the osprey's journey towards the fish. According to (21) this new position of the osprey replaces the prior position if it enhances the value of the goal function.

$$q_{I,J}^{P1} = q_{I,J} + r_{I,J}\,.(SF_{I,J} - E_{I,J}\,.\,q_{I,J}) \tag{19}$$

$$q_{I,J}^{P1} = \begin{cases} q_{I,J}^{P1}, lb_J \le q_{I,J}^{P1} \le ub_J \\ lb_J, \ \ q_{I,J}^{P1} \le lb_J; \\ ub_J, \ \ q_{I,J}^{P1} \ge ub_J \end{cases} \tag{20}$$

$$Q_I = \begin{cases} Q_I^{P1}, \ F_I^{P1} < F_I; \\ Q_I, \ else, \end{cases} \tag{21}$$

where Q_I^{P1} i implicates new positioning of I osprey utilizing 1st phase of OOA, $q_{I,J}^{P1}$ is their J dimension, F_I^{P1} specifies objective function, SF_I denotes selected fish for I osprey, $SF_{I,J}$ is their J dimension, $r_{I,J}$ are random count at [0, 1], $E_{I,J}$ express random numbers from set {1, 2}.

Step 5: Carrying the fish to the suitable position (exploitation)

The osprey brings the fish it has successfully hunted to a safe place so it can be eaten. The second stage of updating the population in OOA is depicted based on the simulation of this osprey's natural behavior. The results of delivering the fish to the proper spot through modeling, which causes slight changes in the osprey's position in the search space, are a stronger exploitation power of the OOA in the local search and convergence towards better solutions near the discovered solutions. To imitate this natural characteristics of ospreys, OOA's design first generates a new random position for each population member that is deemed to be a "suitable position for eating fish" utilizing (22-23). Then, in accordance with (24), if the objective function's is increased in this newly location, it takes the place of the related osprey's old position.

$$q_{I,J}^{P2} = q_{I,J} + \frac{lb_J + r.(ub_J - lb_J)}{T}, I = 1,2,3,..,N, J = 1,2,3,.M, t = 1,2,3,.T \tag{22}$$

$$q_{I,J}^{P2} = \begin{cases} q_{I,J}^{P2}, lb_J \le q_{I,J}^{P2} \le ub_J; \\ lb_J, \ \ q_{I,J}^{P2} \le lb_J; \\ ub_J, \ \ q_{I,J}^{P2} \ge ub_J, \end{cases} \tag{23}$$

$$Q_I = \begin{cases} Q_I^{P2}, \ F_I^{P2} < F_I; \\ Q_I, \ else, \end{cases} \tag{24}$$

Where Q_I^{P2} indicates new positioning of I osprey utilizing 2nd phase of OOA, $q_{I,J}^{P2}$ is its J dimension, F_I^{P2} is its objective function, $r_{I,J}$ implies random count at [0, 1], t implies iteration counter, T implicates total iterations.

Step 6: Termination Criteria

Verify the termination criteria; if the best result is achieved, the process is over; if not, move on to step 3. Fig.2 illustrates the flowchart of Flowchart of Osprey Optimization Algorithm for Optimizing PHNN Weight Parameter.

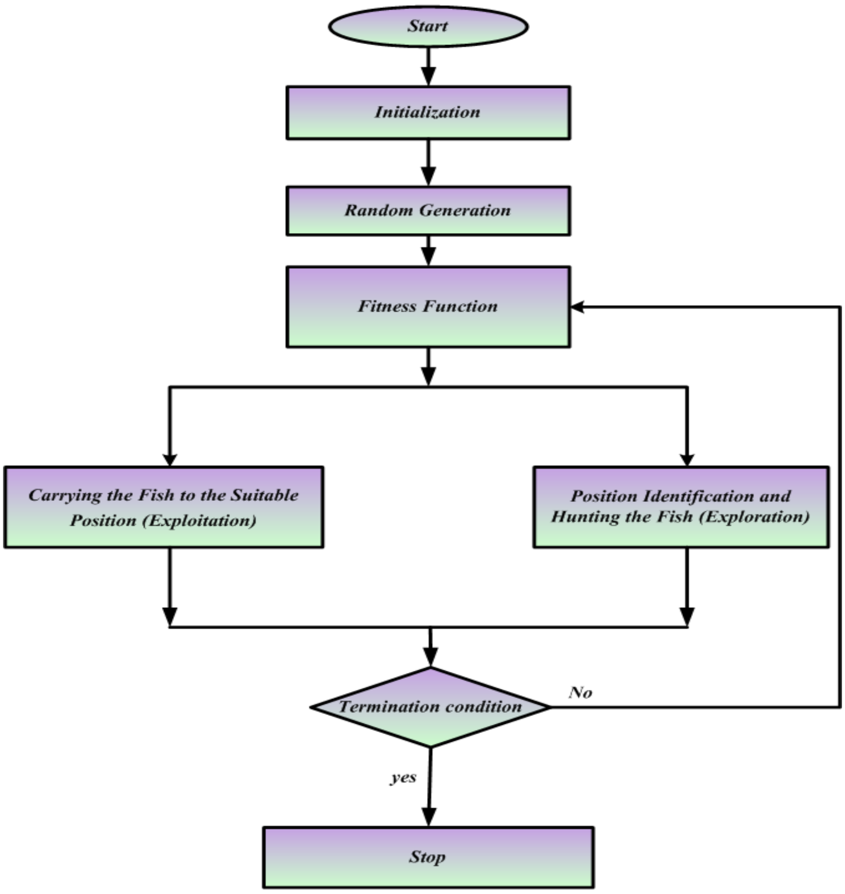

Figure 2: Flowchart of Osprey Optimization Algorithm for Optimizing PHNN Weight Parameter

III. RESULT AND DISCUSSION

UAV technology in smart construction is one of the experimental results of the proposed AUAVT-SC-CM-OOA-PHNN approach. In Implementation work was carried Python and evaluated by using several performance analysing metrics likeaccuracy, computation time, error rate, Fl-score, precision, recall, receiver operating characteristic curve (ROC), Sensitivity and specificity are analysed. The outputs of the AUAVT-SC-CM-OOA-PHNN methodology are compared with existing VAVC-ACFDMT-RNN [11], CD-UAVT-PMRC-ANN [12] and ADL-UAV-BM-CNN [13].

A. Performance measures

To assess performance, the metrics like accuracy, computation time, error rate, Fl-score, precision, recall, receiver operating characteristic curve (ROC), Sensitivity and specificity.

1) Accuracy

This is calculated by eqn (25),

$$accuracy = \frac{TP + TN}{TP + TN + FN + FP} \tag{25}$$

TP epitomizes true positive, TN refers true negative, FP symbolizes false positive, FN signifies false negative.

2) Error Rate

This is determined by equation (26)

$$Error\ Rate = 100 - Accuracy \tag{26}$$

3) F1-Score

This is computed by equation (27),

$$F - score = \frac{TP}{TN + \frac{1}{2}[FN + FP]} \quad (27)$$

4) Precision (P)

It quantifies a number of precise positive prediction using eqn (28),

$$\Pr ecision = \frac{TP}{(TP + FP)} \quad (28)$$

5) Recall

A machine learning model's recall quantifies its ability to identify positive examples. It gauges the probability of obtaining a favourable outcome. That's provided in equation (29)

$$\text{Re}call = \frac{TP}{(TP + FN)} \quad (29)$$

6) Receiver Operating Characteristic Curve (ROC)

ROC provides an overall performance indicator for the whole probable Classification. ROC is expressed in equation (30)

$$ROC = 0.5 \times \left(\frac{T_p}{T_P + F_N} + \frac{T_N}{T_N + F_P} \right) \quad (30)$$

7) Sensitivity

Sensitivity is calculated using the following equation (31)

$$Sensitivity = \frac{T_P}{T_P + F_N} \quad (31)$$

8) Specificity

Specificity is the proportion of real negatives that the approach accurately detects. The answer is found in equation (32),

$$Specificity = \frac{TN}{TN + FP} \quad (32)$$

B. Performance Analysis

The simulation results of the AUAVT-SC-CM-OOA-PHNN technique are shown in Fig 3 to 11. The proposed AUAVT-SC-CM-OOA-PHNN techniques linked to the VAVC-ACFDMT-RNN, CD-UAVT-PMRC-ANN and ADL-UAV-BM-CNN techniques, in that order.

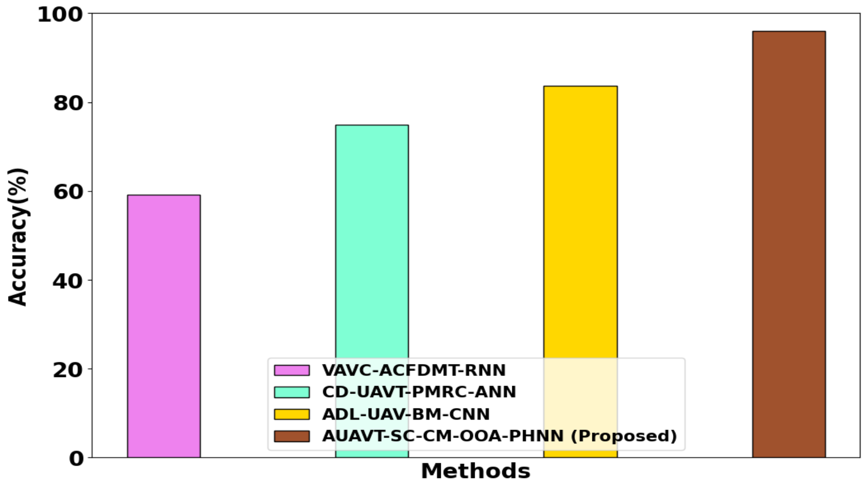

Figure.3. Accuracy analysis

Figure 3exhibits accuracy. The AUAVT-SC-CM-OOA-PHNN method of accuracy is 95%. The existing methods VAVC-ACFDMT-RNN, CD-UAVT-PMRC-ANN and ADL-UAV-BM-CNN the accuracy become 60%, 75% and 85%. The proposed AUAVT-SC-CM-OOA-PHNN reaches better accuracy.

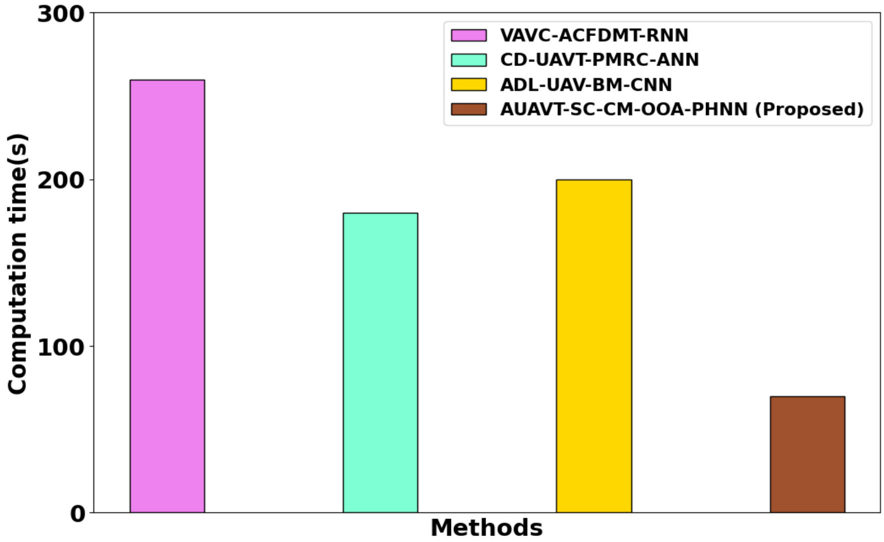

Fig 4: Performance of Computation time

Fig 4 reveals Computation time. The AUAVT-SC-CM-OOA-PHNN method of Computation time is 80s. The existing methods VAVC-ACFDMT-RNN, CD-UAVT-PMRC-ANN and ADL-UAV-BM-CNN the Computation time become 260s, 190s and 200s. The proposed AUAVT-SC-CM-OOA-PHNN method shows lower computation time.

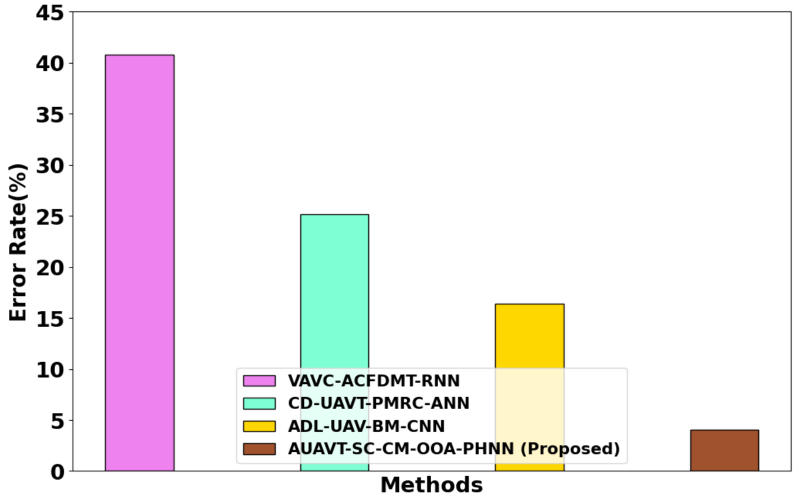

Figure5: Error Rate estimation

Figure5 depicts performance of error rate. The AUAVT-SC-CM-OOA-PHNN method of error rate is 5%. The existing methods VAVC-ACFDMT-RNN, CD-UAVT-PMRC-ANN and ADL-UAV-BM-CNN the error rate become 41%, 25% and 17%. The proposed AUAVT-SC-CM-OOA-PHNN achieves less error rate.

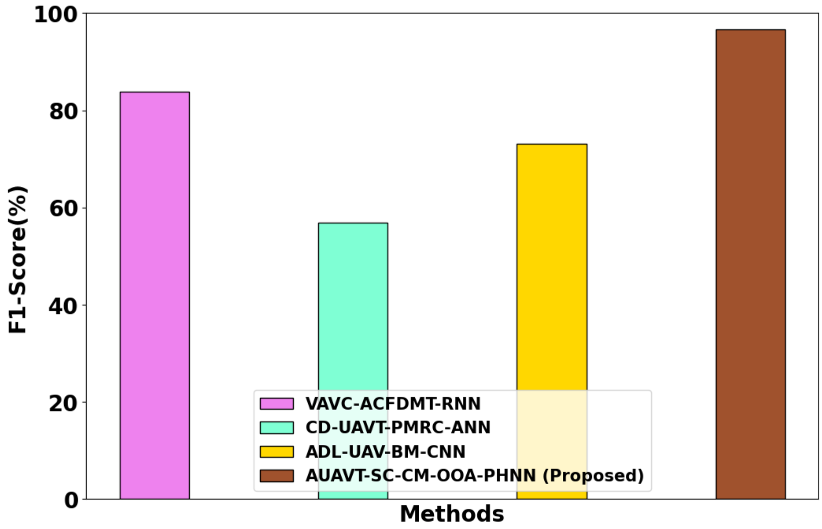

Figure6: F1-Score assessment

Figure6 shows F1-Score evaluation. The AUAVT-SC-CM-OOA-PHNN method of F1-Score is 95%. The existing methods VAVC-ACFDMT-RNN, CD-UAVT-PMRC-ANN and ADL-UAV-BM-CNN the F1-Score become 83%, 55% and 75%. The proposed AUAVT-SC-CM-OOA-PHNN reaches better F1-Score over the existing models.

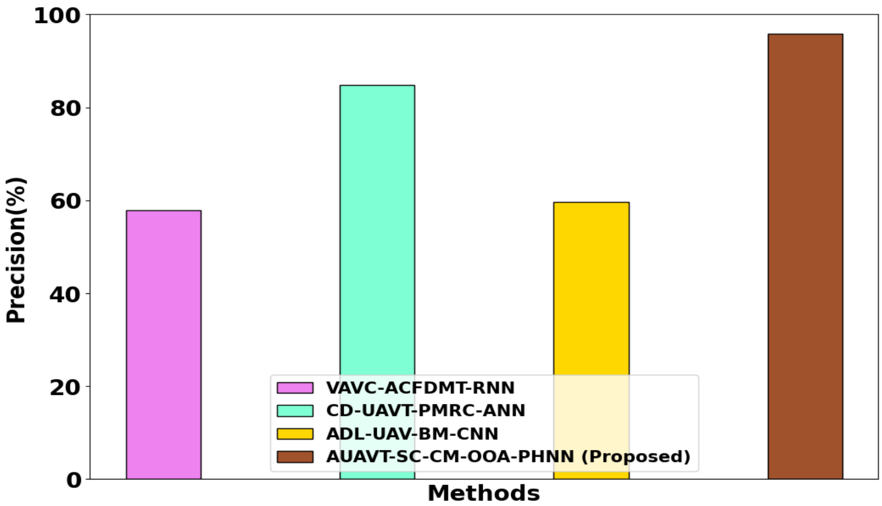

Figure7: Precision estimation

Figure7 displays precision estimation. The AUAVT-SC-CM-OOA-PHNN method of precision is 95%. The existing methods VAVC-ACFDMT-RNN, CD-UAVT-PMRC-ANN and ADL-UAV-BM-CNN the Precision become 58%, 85% and 60%. The proposed AUAVT-SC-CM-OOA-PHNN reaches greater Precision than the existing models.

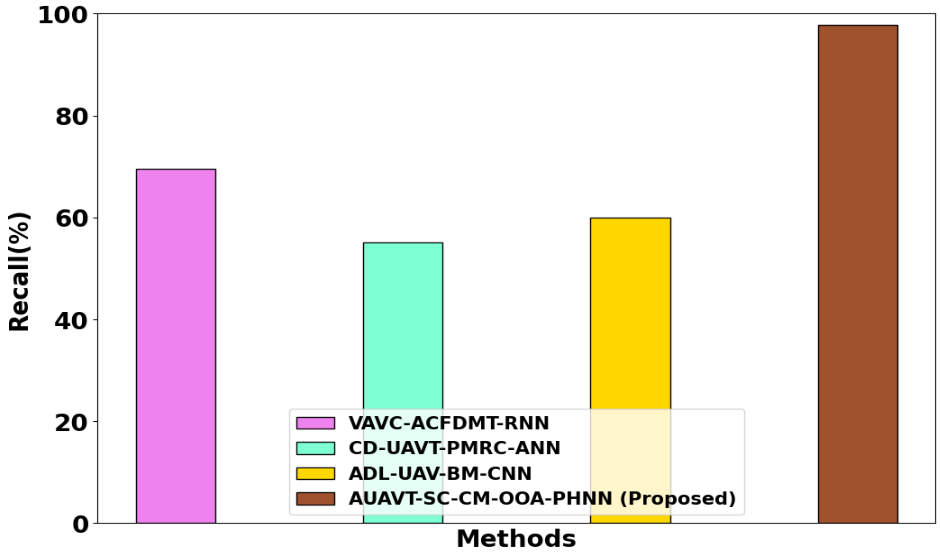

Figure8: Recall evaluation

Figure8 depicts recall evaluation. The AUAVT-SC-CM-OOA-PHNN method of recall is 98%. The existing methods VAVC-ACFDMT-RNN, CD-UAVT-PMRC-ANN and ADL-UAV-BM-CNN the recall become 70%, 55% and 60%. The proposed AUAVT-SC-CM-OOA-PHNN attains greater recall than the existing models.

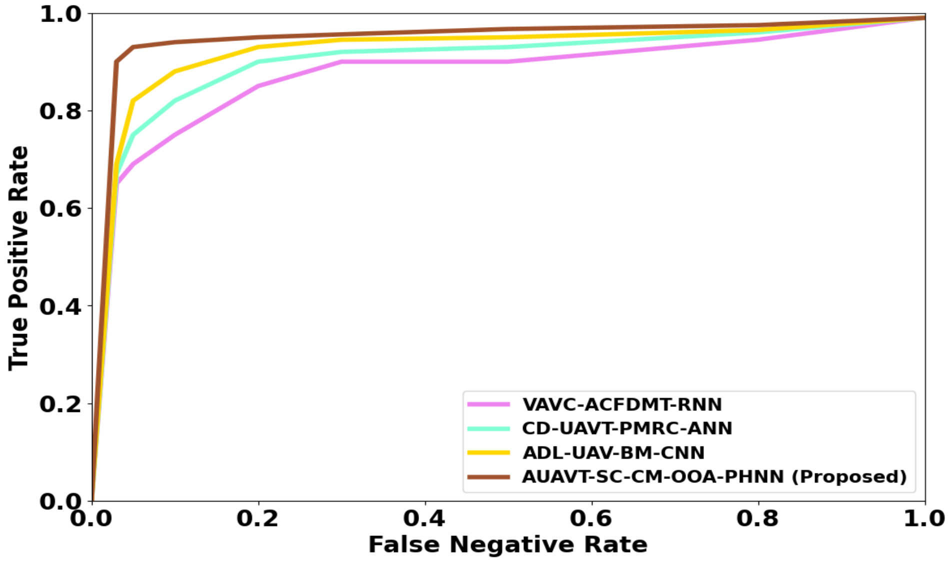

Figure 9: Performance Analyses of Receiver Operating Characteristic Curve (ROC)

The performance analyses of ROC are shown in fig 9. Each point on the curve represents a different threshold value, and the curve is created by connecting these points. The higher ROC indicates better performance in distinguishing between positive and negative instances. The proposed AUAVT-SC-CM-OOA-PHNN methods the ROC provides high UAV technology in smart construction compared with other existing methods. The existing methods like VAVC-ACFDMT-RNN, CD-UAVT-PMRC-ANN and ADL-UAV-BM-CNN the ROC become lower compared with the proposed AUAVT-SC-CM-OOA-PHNN technique.

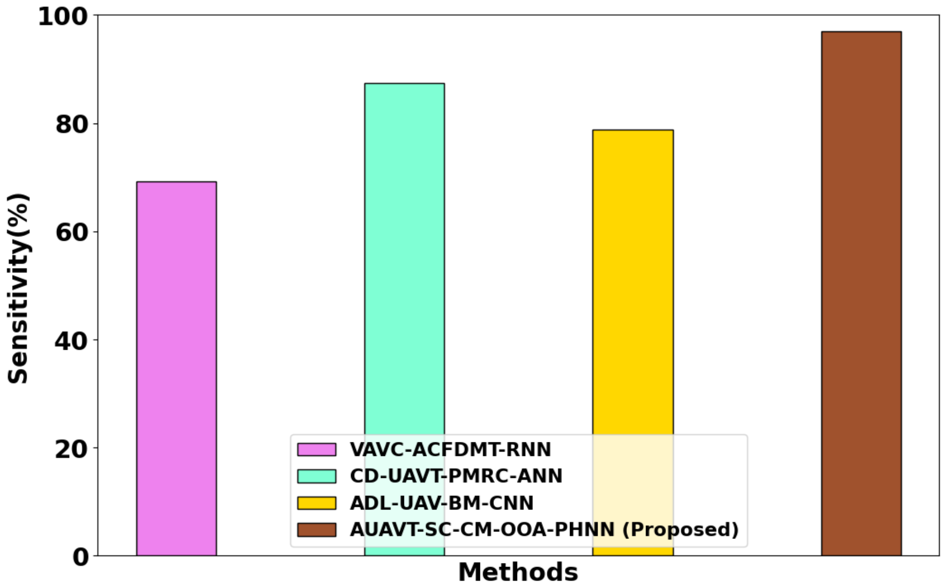

Fig 10: Sensitivity evaluation

Figure10 portrays sensitivity evaluation. The AUAVT-SC-CM-OOA-PHNN method of sensitivity is 98%. The existing methods VAVC-ACFDMT-RNN, CD-UAVT-PMRC-ANN and ADL-UAV-BM-CNN the sensitivity become 70%, 85% and 80%. The proposed AUAVT-SC-CM-OOA-PHNN attains greater sensitivity than the existing models.

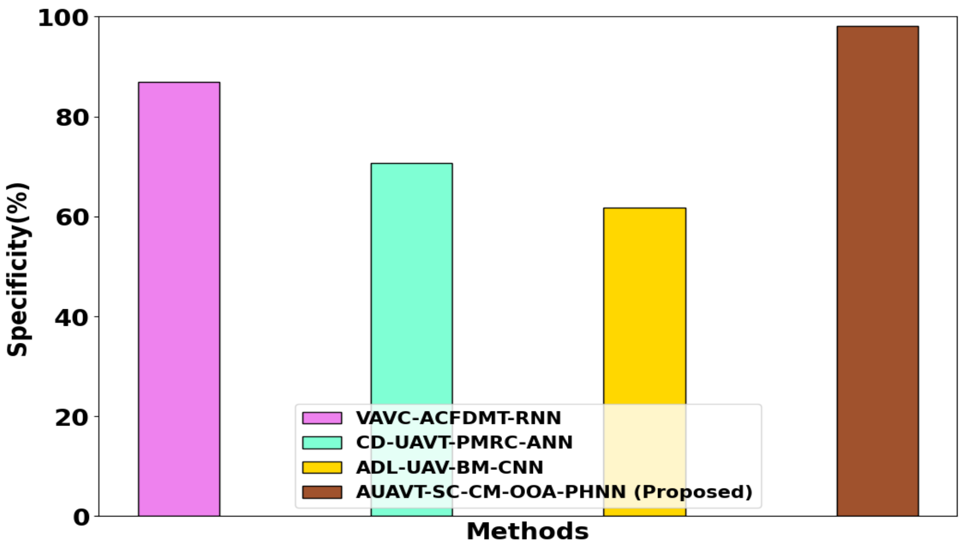

Figure 11: Specificity estimation

Figure11 shows Specificity estimation. The AUAVT-SC-CM-OOA-PHNN method of Specificity is 98%. The existing methods VAVC-ACFDMT-RNN, CD-UAVT-PMRC-ANN and ADL-UAV-BM-CNN the Specificity become 87%, 70% and 60%. The proposed AUAVT-SC-CM-OOA-PHNN method shows higher Specificity compare with existing method.

C. Discussion

The proposed AUAVT-SC-CM-OOA-PHNN method achieves superior performance compared to existing methods in terms of accuracy, computation time, error rate, F1-Score, precision, recall, sensitivity, and specificity. The accuracy of AUAVT-SC-CM-OOA-PHNN is 95%, significantly higher than VAVC-ACFDMT-RNN (60%), CD-UAVT-PMRC-ANN (75%), and ADL-UAV-BM-CNN (85%). Similarly, AUAVT-SC-CM-OOA-PHNN exhibits lower computation time (80s) analyzed to the existing models (190s to 260s). The AUAVT-SC-CM-OOA-PHNN method also demonstrates a lower error rate (5%) and a higher F1-Score (95%) compared to the existing techniques. Furthermore, AUAVT-SC-CM-OOA-PHNN achieves higher precision (95%), recall (98%), sensitivity (98%), and specificity (98%) compared to the existing methods. The ROC analysis in Fig 9 further confirms the superiority of AUAVT-SC-CM-OOA-PHNN, demonstrating a significantly higher ROC curve compared to the existing models. These findings suggest that AUAVT-SC-CM-OOA-PHNN is a highly effective method for UAV technology in smart construction applications.

IV. CONCLUSION

In this manuscript, application of UAV technology in smart construction in construction monitoring using OOA-PHNN (AUAVT-SC-CM-OOA-PHNN) was successfully implemented. The proposed AUAVT-SC-CM-OOA-PHNN approach is implemented in Python.Initially, data are collected from DVBI-CVVL-RSE dataset. This method extracts the features and supplied to the pseudo-hamiltonian neural networks (PHNN) is used to estimate the class and location of construction building site in a full image or video. The UAV is using to capture the photo of construction site and used to track in construction site work progress in real time. It overcomes the issues of inadequate study in the categorization of existing data, and attains greater outputs of drone view building identification data than existing network models. The evaluation results demonstrate substantial improvements over established methods such as VAVC-ACFDMT-RNN, CD-UAVT-PMRC-ANN and ADL-UAV-BM-CNN, with accuracy increases of 29%, 24.5% and 20% respectively. Specifically, it showcases 30%, 20% and 25.5% reductions in computation time, along with 27.5%, 25.5% and 22% improvements in accuracy compared to other existing methods, demonstrating predictive performance. Further data extraction may be necessary in the future to enhance classification performance on UAV technology in smart construction images.

REFERENCE

[1] Chun, P. J., Dang, J., Hamasaki, S., Yajima, R., Kameda, T., Wada, H., ... & Nagatani, K. (2020). Utilization of unmanned aerial vehicle, artificial intelligence, and remote measurement technology for bridge inspections. *Journal of Robotics and Mechatronics*, *32*(6), 1244-1258.

[2] Sreenath, S., Malik, H., Husnu, N., & Kalaichelavan, K. (2020). Assessment and use of unmanned aerial vehicle for civil structural health monitoring. *Procedia Computer Science*, *170*, 656-663.

[3] Lei, B., Ren, Y., Wang, N., Huo, L., & Song, G. (2020). Design of a new low-cost unmanned aerial vehicle and vision-based concrete crack inspection method. *Structural Health Monitoring*, *19*(6), 1871-1883.

[4] Mohamed, N., Al-Jaroodi, J., Jawhar, I., Idries, A., & Mohammed, F. (2020). Unmanned aerial vehicles applications in future smart cities. *Technological forecasting and social change*, *153*, 119293.

[5] Jacob-Loyola, N., Muñoz-La Rivera, F., Herrera, R. F., & Atencio, E. (2021). Unmanned aerial vehicles (UAVs) for physical progress monitoring of construction. *Sensors*, *21*(12), 4227.

[6] Sivakumar, M., & Tyj, N. M. (2021). A literature survey of unmanned aerial vehicle usage for civil applications. *Journal of Aerospace Technology and Management*, *13*, e4021.

[7] Casierra, C. B. G., Sánchez, C. G. C., García, J. F. C., & La Rivera, F. M. (2022). Methodology for Infrastructure Site Monitoring using Unmanned Aerial Vehicles (UAVs). *International Journal of Advanced Computer Science and Applications*, *13*(3).

[8] Antonenko, I. M. P. (2022). Unmanned aerial vehicles as educational technology systems in construction engineering education. *Journal of information technology in construction*, *27*.

[9] Zhu, H., Hwang, B. G., Ngo, J., & Tan, J. P. S. (2022). Applications of smart technologies in construction project management. *Journal of Construction Engineering and Management*, *148*(4), 04022010.

[10] Outay, F., Mengash, H. A., & Adnan, M. (2020). Applications of unmanned aerial vehicle (UAV) in road safety, traffic and highway infrastructure management: Recent advances and challenges. *Transportation research part A: policy and practice*, *141*, 116-129.

[11] Liang, H., Lee, S. C., Bae, W., Kim, J., & Seo, S. (2023). Towards UAVs in construction: advancements, challenges, and future directions for monitoring and inspection. *Drones*, *7*(3), 202.

[12] Han, D., Lee, S. B., Song, M., & Cho, J. S. (2021). Change detection in unmanned aerial vehicle images for progress monitoring of road construction. *Buildings*, *11*(4), 150.

[13] Kung, R. Y., Pan, N. H., Wang, C. C., & Lee, P. C. (2021). Application of deep learning and unmanned aerial vehicle on building maintenance. *Advances in Civil Engineering*, *2021*, 1-12.

[14] Mahajan, G. (2021). Applications of drone Technology in Construction Industry: A study 2012-2021. *International Journal of Engineering and Advanced Technology*, *11*(1), 224-239.

[15] Namian, M., Khalid, M., Wang, G., & Turkan, Y. (2021). Revealing safety risks of unmanned aerial vehicles in construction. *Transportation research record*, *2675*(11), 334-347.

[16] Hatoum, M. B., & Nassereddine, H. (2022). The use of Drones in the construction industry: Applications and implementation. In *ISARC. Proceedings of the International Symposium on Automation and Robotics in Construction* (Vol. 39, pp. 542-549). IAARC Publications.

[17] York, D. D., Al-Bayati, A. J., & Al-Shabbani, Z. Y. (2020, March). Potential applications of uav within the construction industry and the challenges limiting implementation. In *Construction Research Congress 2020* (pp. 31-39). Reston, VA: American Society of Civil Engineers.

[18] Shirowzhan, S., Tan, W., & Sepasgozar, S. M. (2020). Digital twin and CyberGIS for improving connectivity and measuring the impact of infrastructure construction planning in smart cities. *ISPRS International Journal of Geo-Information*, *9*(4), 240.

[19] Jeelani, I., & Gheisari, M. (2021). Safety challenges of UAV integration in construction: Conceptual analysis and future research roadmap. *Safety science*, *144*, 105473.

[20] Pan, Y., & Zhang, L. (2023). Integrating BIM and AI for smart construction management: Current status and future directions. *Archives of Computational Methods in Engineering*, *30*(2), 1081-1110.

[21] Syed, F., Gupta, S. K., Hamood Alsamhi, S., Rashid, M., & Liu, X. (2021). A survey on recent optimal techniques for securing unmanned aerial vehicles applications. *Transactions on Emerging Telecommunications Technologies*, *32*(7), e4133.

[22] Sestras, P., Roșca, S., Bilașco, Ș., Naș, S., Buru, S. M., Kovacs, L., ... & Sestras, A. F. (2020). Feasibility assessments using unmanned aerial vehicle technology in heritage buildings: Rehabilitation-restoration, spatial analysis and tourism potential analysis. *Sensors*, *20*(7), 2054.

[23] Mohsan, S. A. H., Othman, N. Q. H., Li, Y., Alsharif, M. H., & Khan, M. A. (2023). Unmanned aerial vehicles (UAVs): Practical aspects, applications, open challenges, security issues, and future trends. *Intelligent Service Robotics*, *16*(1), 109-137.

[24] Martinez, J. G., Gheisari, M., & Alarcón, L. F. (2020). UAV integration in current construction safety planning and monitoring processes: Case study of a high-rise building construction project in Chile. *Journal of Management in Engineering*, *36*(3), 05020005.

[25] Hamledari, H., & Fischer, M. (2021). Construction payment automation using blockchain-enabled smart contracts and robotic reality capture technologies. *Automation in Construction*, *132*, 103926.

[26] Al-Turjman, F., Zahmatkesh, H., Al-Oqily, I., & Daboul, R. (2020). Optimized unmanned aerial vehicles deployment for static and mobile targets' monitoring. *Computer Communications*, *149*, 27-35.

[27] https://jcwchen.github.io/DVBI/

[28] Yu, Y., Li, Q., & Zhang, H. (2023). Unscented trainable Kalman filter based on deep learning method considering incomplete information. *IEEE Access*.

[29] Dong, F., Yang, J., & Cai, Y. (2023). Multi-objective matched synchrosqueezing chirplet transform for fault feature extraction from marine turbochargers. *IEEE Access*.

[30] Eidnes, S., & Lye, K. O. (2024). Pseudo-Hamiltonian neural networks for learning partial differential equations. *Journal of Computational Physics*, *500*, 112738.

[31] Dehghani, M., & Trojovský, P. (2023). Osprey optimization algorithm: A new bio-inspired metaheuristic algorithm for solving engineering optimization problems. *Frontiers in Mechanical Engineering*, *8*, 1126450.