International Journal of Computational and Experimental Science and ENgineering (IJCESEN)

Vol. 11-No.1 (2025) pp. 1314-1329

http://www.ijcesen.com

ISSN: 2149-9144

Research Article

AI-Powered Real-Time Runway Safety: UAV-Based Video Analysis with ICSO-Enhanced Deep Learning

V. Thamilarasi [1]*, R. Hema[2], A. Noble Mary Juliet[3], Adlin Sheeba[4], Gauri Ghule[5], A. Raja[6]

[1]Assistant Professor of Computer Science, Sri Sarada College for Women (Autonomous), Salem, Tamilnadu, India.
*** Corresponding Author Email:** tamilomsiva@gmail.com – **ORCID:** 0000-0002-5866-0074

[2]Assistant Professor, Department of Computer Science, SDNB Vaishnav College for Women, Chennai, Tamilnadu, India.
Email: hemaramji@sdnbvc.edu.in – **ORCID:** 0000-0001-8587-8880

[3]Department of Computer Science and Engineering, Dr.Mahalingam College of Engineering and Technology, Pollachi, Tamilnadu, India.
Email: cse.julie@gmail.com - **ORCID:** 0000-0003-3410-4994

[4]Professor, Department of Computer Science and Engineering, St. Joseph's Institute of Technology, Chennai, Tamilnadu, India.
Email: adlinsheeba78@gmail.com - **ORCID:** 0000-0002-7428-8575

[5]Assistant Professor, Department of Electronics and Telecommunication, VIIT college of Engineering, Pune, India.
Email: gauri.ghule@viit.ac.in - **ORCID:** 0000-0003-3118-6533

[6]Assistant Professor, Department of Computer Science and Engineering (Cyber Security), United Institute of Technology, Coimbatore, India.
Email: rajagct@gmail.com - **ORCID:** 0009-0005-6291-4670

Article Info:

DOI: 10.22399/ijcesen.1184
Received : 30 November 2024
Accepted : 22 February 2025

Keywords :

Runway Safety,
Runway Crack,
Runway Friction,
Video Analysis,
Flight Safety Landing.

Abstract:

In the aviation sector, ensuring safe landings while prioritizing the safety of runways is crucial to prevent accidents and incidents during the landing phase of flights. However, many studies analyzing unsafe events, such as runway cracks or inadequate friction, often fail to quantify their impacts on flight safety during landing. In airport pavement management systems (APMS), the condition of the runway surface is a critical factor in ensuring the operational safety of aircraft during take-off and landing. Therefore, it is essential to provide pilots with reports on runway conditions, including measurements of surface performance, to support informed decision-making. To tackle these challenges, we propose a real-time automatic monitoring system for runway safety utilizing video analysis. Specifically, we employ a time-series analysis approach using the improved chameleon swarm optimization (ICSO) algorithm to mine runway surface characteristics from real-time video data captured by unmanned aerial vehicles (UAVs). Subsequently, we introduce the fuzzy reinforced polynomial neural network (FR-PNN) to detect risks in runway surface characteristics, enabling automatic monitoring to enhance the safety of aircraft landings. Finally, the effectiveness of the proposed system is validated using real-time videos obtained from Bechyne military airport, located in Bohemia. This system aims to improve runway safety by providing timely and accurate assessments of runway conditions, thereby facilitating safer landings for aircraft.

1. Introduction

Aviation infrastructure relies on runway safety surveillance systems to prevent accidents and ensure aircraft safety during flight operations [1]. Runway monitoring systems prevent runway incursions, identify dangers, and maintain operational integrity in the aviation business, where safety is vital [2]. These technologies continuously monitor runway situations, detect anomalies, and warn air traffic control officers and airport staff in real time, improving situational awareness and reducing risks [3]. Airport safety relies on runway monitoring systems to protect travelers, crew, and ground staff. These systems detect FOD, wildlife encroachment, and unlawful entry using modern sensors, security cameras, and data analytics. They also help the control of air traffic towers, ground-based control units, and airport management centers communicate and respond to safety incidents [4,5]. Runway safety monitoring systems are in high demand as airports worldwide endure unprecedented flight traffic and operational complexity [6]. To handle new safety issues, these systems must adapt to changing aviation standards, technology, and regulations [7]. As smart airports and technological advancement programs grow, runway monitoring systems are linked into airport administration frameworks, enabling data sharing, connectivity, and decision support across operational domains [8]. Airport authorities and aviation stakeholders face many obstacles in runway safety monitoring due to the constantly changing and high-stakes nature of the airport's operations [9]. A major issue is the necessity for extensive surveillance coverage of airport runways, taxiways, aprons, and approaches zones. Achieving ubiquitous visibility requires sophisticated sensor networks and surveillance systems that can capture, process, and analyze massive amounts of data in real time [10].

Airports' many operational operations and environmental conditions make safety-critical incident detection and classification difficult [11]. Runway monitoring systems face runway incursions, airplane overruns, wildlife dangers, and bad weather [12]. Safety events must be identified quickly and accurately to enable proactive response and avoid small incidents from becoming severe accidents. Runway monitoring systems find it difficult to integrate several data sources, sensor modalities, and communication protocols [13]. Strong integration frameworks, established protocols, and collaboration between airport operators, airlines, regulatory agencies, and technology suppliers are needed to integrate, share, and support data across operational domains. Video analytics technology has transformed aircraft safety and surveillance by enabling real-time monitoring, analysis, and decision support [14]. Traditional CCTV systems were excellent in capturing visual data, but they lacked the intelligence and analytical capacity to extract actionable insights from complicated video streams. Advanced video analytics technologies powered by machine learning, deep learning, and computer vision algorithms have changed airport security and runway surveillance [15]. Recent breakthroughs in image processing, computer vision and pattern recognition allow for the building of sophisticated video surveillance systems that can detect, track, and evaluate items of interest with unmatched precision and efficiency. These devices can perform all this rapidly and accurately. CNNs, RNNs, and GANs can recognize photos, detect objects, analyze behavior, and identify video stream anomalies [16].

Deep learning algorithms will let airports recognize and respond to safety-critical situations in real time [17]. This will reduce dangers and keep planes safe. Airports can maximize operations and safety with deep learning-based video analytics solutions. These monitoring technologies track runway breaches, foreign objects, animals, and illegal entry. Deep learning is essential for live video analytics to monitor runway safety. Deep learning systems employ hierarchy models for raw input data instead of handmade features and established guidelines for image processing [18]. This contrasts with old approaches. Due to their superior object identification, recognition, and semantic segmentation, CNNs are ideal for airport photo analysis. CNNs recognize things by semantic segmentation. Deep learning algorithms are scalable and versatile, making them suitable for runway safety monitoring expanding issues and complexities [19]. Deep learning-based video analytics can increase awareness of situations, making choices, and airport risk mitigation. Finding subtle runway conditions and studying complex behavior patterns achieves this. In addition to CNNs, RNNs and LSTMs may perform analyses of time and sequence modeling [20]. They can forecast future behavior and occurrences based on past observations. In order to guarantee safety, airport management is required to keep a close check on runway performance and make sure that surfaces are properly maintained. We suggest an innovative real-time automated runway safety monitoring system designed to mitigate potential hazards through video analysis. The key contributions of our work are outlined below:

Using a time-series analysis methodology, we leverage the improved chameleon swarm optimization (ICSO) algorithm to extract crucial runway surface characteristics from live video feeds captured by UAVs. We implement the fuzzy reinforced polynomial neural network (FR-PNN) for the identification of risks associated with runway surface conditions. This automated detection capability enhances safety measures during aircraft landings by promptly identifying and alerting operators to potential safety concerns. To validate the efficacy of our proposed system, we conduct real-time testing using video data collected from Bechyne Military Airport, situated in southern Bohemia. Through this validation process, we

assess the system's performance under real-world conditions, ensuring its reliability and effectiveness in enhancing runway safety.
The rest of this paper is organized as follows. In Section 2, we present a thorough review of the existing literature concerning the real-time automated runway safety monitoring system. Section 3 delves into the research methodologies and principles employed in this study, including the VR based video analysis. Moving forward, Section 4 conducts comparative analysis and provides a comprehensive assessment of the prediction outcomes using various metrics. In Section 5, the conclusions and expectations of this research are discussed.

2. Literature Review

2.1 State-of-art studies

Li et al. 2023 [21] propose the interpretable model, IMTCN, predicts flight safety occurrences based on flight data with high interpretability to address the aviation industry's important flight safety issue. IMTCN uses numerous TCNs to collect local representations and protracted effective histories from varied multivariate flight data for multi-scale time series categorization. Integrating CAM with TCNs improves model interpretability by identifying flight characteristics and moments that cause safety issues. IMTCN outperforms baseline approaches in exceedance classification and safety incident prediction on an actual database of 37,943 Airbus A320 aircraft flights, and case studies show its exceptional interpretability for flight safety analysis. IMTCN improves flight safety prediction methods by combining accuracy and interpretability, giving aviation stakeholders actionable insights.
Farhadmanesh et al. 2023 [22] tackle the issue of flight operations recording at most U.S. airports without control towers. The specialists made an electronic video-based observing framework to identify general flying airplane leaving and score tasks at non-transcended air terminals. The framework has three modules: airplane ID, following, and exercises count and grouping. The specialists advanced camera arrangements and utilized state of the art AI and profound learning ways to deal with remove direction data required for activities count and classification. The framework performed well at five non-transcended air terminals, with an accuracy of 95%. Deep-neural-network-based aircraft detector and image-correlation-based aircraft tracker ensured high accuracy and real-time implementation, essential for flight surveillance and management at non-towered airports.
Sun et al. 2023 [23] proposed an Intelligent monitoring systems, notably in airport security, are essential for risk the avoidance and management in civil aviation. High-resolution video surveillance systems cover huge airport regions, but the volume of security footage makes manually monitoring and real-time tracking difficult. Utilizing AI to recognize dangerous signs in security films and give constant early admonitions is pivotal for brilliant air terminal observing. This study depicts a savvy observation framework for air terminal security that utilizes the Just go for it calculation to distinguish unapproved targets. This exploration gives a specialized premise to the air terminal's modern observation stage, upgrading air terminal security tasks' capacity to rapidly distinguish and moderate dangers.
Jin et al. 2024 [24] mentioned A-CDM uses flight support node information as a main data source to improve airport operational efficiency. Traditional manual node information collection methods are inefficient due to accuracy as well as speed issues. Some ground-based operation data is inaccessible automatically. This work suggests A-CDM time node collecting via a video analytics service system to address this issue. The paper describes the algorithm repository's technologies, components, implementation, and future implications. This technology automates the gathering of landmark event dates and times during flight airport turnaround times to circumvent manual gathering of information limitations and enable smart airport growth that benefits airports economically and socially.
Soriano et al. 2023 [25] mention in educational research, user-simulation interaction is becoming increasingly important, especially in simulation-based instruction and technology that is immersive. Manual instantaneous evaluation or post-event video analysis is laborious and subjective ways to investigate such interactions. Surveys and questionnaires are widespread yet provide qualitative data. EDUSIM analyzes screen-recorded videos of participants interacting with virtual environments to provide empirical information on their interaction patterns in preset locations. EDUSIM automates navigation data extraction using multiple classifications Convolutional Neural Networks and a model that uses binary classification to recognize poor input video data. In immersive simulation-based instructional components in an undergraduate database course, the tool is tested. EDUSIM analyzes screen records and compares them to manual video analysis. EDUSIM shows its potential to expedite user-

simulation interaction analysis, making simulation-based learning environment educational research more efficient and objective.

Han et al. 2024 [26] discuss how current deep-learning classifiers fail to recognize rogue drones, particularly those that blend into the backdrop or operate in low light, which threaten vital infrastructures. The authors offer RANGO, a drone recognition algorithm that can recognize drones even in difficult to distinguish target from background settings. After PREP, RANGO uses various convolution kernels to determine drone presence. RANGO outperforms other methods on a broad dataset of birds and planes. RANGO outperforms YOLOv5 by 6.6% on photos with concealed drones and by 2.2% on ordinary datasets, proving its efficacy in both difficult and broad settings. RANGO's revolutionary drone detection method improves critical infrastructure security.

Balasubramanian et al. 2023 [27] to stop the spread of COVID-19, mask-wearing has become essential. The widespread use of masks makes it difficult for surveillance and safety systems to identify those wearing them. The solutions use ResNet152V2 and VGG16 architectures to monitor still photos and live video streams in real time. Real-time face detection using OpenCV ensures mask placement across the nose, mouth, and chin. ResNet152V2 detects faces robustly, whereas a head-based classification algorithm separates masked and unmasked faces. To improve video stream performance, computer vision is used. The ResNet152V2 model performs well in mask identification tasks, with reliability, precision, and F1-score rates of 99.1%, 99.2%, and 99.1%, respectively.

Ran et al. 2023 [28] proposed Airport flight turnarounds depend on accurately recording the beginning and end times of each node to meet established timeframes and streamline following flight tasks. Manual turnaround node time recording has proven inefficient and limited data organization and display. The approach improves the model's accuracy and inference speed using YOLOv5s-based detection network with attention methods and Faster Net as the backbone. Dual-perspective coordinating for aircraft places, adaptive concealment, and other methods allow the system to make logical node status decisions. The proposed detection network outperforms baseline approaches with a 20fps inference time and 0.08 mAP@.5:.95 detection accuracy on a self-built apron dataset. The technique reduces average node time error by 60–120 seconds compared to human methods, improving airport flight turnaround efficiency. Li et al. 2023 [29] in the work mention Pilot behavior is crucial to flight safety analysis. Many studies of dangerous incidents, such runway overruns, fail to quantify pilot behavior's impact on flight safety. The study recovers pilot behavioral trends from pilot operational information using time series clustering. A case study shows three pilot behavioral features in the selected fleet, principally variations in pilot response time post-VR and control column input speed. Real flight information across airline settings is used to add pilot behavior traits, improving risk assessments for other dangerous incidents including hard landings and tail impacts.

Zhao et al. 2023 [30] proposed during arrival and landing maneuvers, the Navaid lighting system is crucial to aircraft flight safety. Maintaining its flawless operation is crucial to aircraft landing and taking off safety. However, the civil aviation industry's growing demands have outpaced manual Navaid lighting inspection procedures. Thus, automating Navaid lighting equipment monitoring is essential for system reliability. Data mining algorithms are used to design, develop, and implement a runway Navaid lighting monitoring system. To ensure safety, the NAV light tracking system monitors all airport lights, detecting any unusual light patterns or variations that may indicate navigation light difficulties. This proactive approach allows airport officials to quickly handle emergent issues before they worsen, preventing accidents. The design phase includes software development for this monitoring system to strengthen Navaid lighting systems and ensure flight safety.

2.2 Problem description

A real-time automatic monitoring is crucial for ensuring the safety of aircraft landings. This system provides continuous surveillance of runway conditions, allowing for early detection and mitigation of potential safety hazards. By employing video analysis algorithms, various runway surface characteristics and risks can be swiftly identified, such as debris, wildlife intrusion, or surface anomalies. This proactive approach enables immediate action to be taken to prevent accidents. Additionally, the system can adapt to dynamic changes in runway conditions, such as weather fluctuations or human interference, ensuring that safety measures remain effective at all times. Automation of the monitoring process reduces reliance on manual inspections, providing consistent and reliable safety oversight without human intervention. The data collected from runway surveillance cameras allows for informed decision-making regarding maintenance, repairs, and safety protocols, in compliance with aviation regulations. In Maslan et al. [31] concentrated on a safe aviation travel, it is imperative that distress on an airport pavement be promptly detected and recognized. Because of its vastness, an actual physical check of the airport maneuvering zones is conducted on a regular basis for this reason, which could take some time. Among the contemporary methods for UAV footage combined with automated assessment expedites this process. The dataset for the preparation, approval, and testing of a Yolov2 object indicator was made utilizing the ethereal picture information that were gathered during airplane at the predetermined elevation over the runway and handled utilizing business multi-view remaking programming.

The effectiveness of a real-time monitoring system heavily relies on the quality of images or video frames captured by surveillance cameras. Poor lighting conditions, inclement weather, or camera malfunctions can result in blurry or distorted images. These visual impairments make it challenging for the system to accurately identify runway hazards, as important details may be obscured or indiscernible. The high dimensionality of data generated by runway surveillance cameras poses challenges for real-time processing and analysis. Processing large volumes of image or video data in real-time requires significant computational resources and may lead to delays or inefficiencies. Additionally, managing massive amounts of data can be resource-intensive, necessitating sophisticated data management techniques. Conversely, false negatives or missed detections can also pose significant risks to runway safety. If the monitoring system fails to identify actual hazards or anomalies, it may result in undetected safety threats and potential accidents during aircraft landings. Reducing the false alarm rate requires continuous system optimization and algorithm refinement. In order to avoid mishaps and problems during the landing phase of flights, the aviation industry must prioritize the safety of runways while guaranteeing safe landings. But most analyses of hazardous events such as cracks in the runway or inadequate friction and do not quantify to what extent of impact they contribute to landing flight safety. As per airport pavement management systems (APMS), the condition of a runway is vital in ensuring an aircraft's operational safety while taking off and landing. The subsequent research aims utilized to solve major challenges compiled from literature review by concentrating on quality improvement, accuracy in feature extraction, efficient processing of data, and minimizing false alarms. Design algorithms and methods for improving the visual quality and resolution of images from surveillance cameras in different environmental conditions, such as low illumination, poor weather, and occlusion.

2.Investigate advanced computer vision and image processing methods to improve the accuracy and robustness of feature extraction from runway surveillance images, considering complex backgrounds, occlusions, and noise.

3.Design effective data processing methods and algorithms to manage the high dimensionality of image and video data produced by runway surveillance cameras in real-time with minimal computational overhead and resource usage.

4.Explore novel ML and anomaly detection approaches to reduce false positive and false alarm rates in runway safety monitoring systems, ensuring reliable detection of actual hazards while minimizing unnecessary alerts and alarms.

3. Proposed methodology

The system architecture of the proposed real-time automatic monitoring system for runway risk detection is depicted in figure 1. Our suggested approach involves several steps to develop this system for enhancing runway safety through video analysis. Initially, video data is collected from runway cameras, followed by preprocessing to enhance its quality. Later on, computer vision algorithms are employed to detect and track different objects on the runway, including automobiles, aircraft, and other appropriate entities. At the same time, the system assesses the runway conditions by classifying and examining surface features, including wetness, dryness, or icy surfaces. Additionally, the system monitors the paths of identified objects and alerts in the event of any violation of safety rules, including runway incursions or possible crashes. It also provides decision support and risk assessment scores to pilots and air traffic controllers, aiding them in making informed decisions. The correctness of the system is rigorously tested, and seamlessly integrated with the existing air traffic management infrastructure. Additionally, the system analyzes the details of the runway captured in the video data to identify potential risks. A time-series analysis method, employing the improved chameleon swarm optimization (ICSO) algorithm, is employed to extract runway surface properties from the real-time video data obtained via UAVs. Subsequently, the fuzzy reinforced polynomial neural network (FR-PNN) is introduced to identify hazards in the runway surface properties effectively. This automated observation system aims to enhance the safety of airplane landings by promptly identifying and addressing potential risks present on the runway.

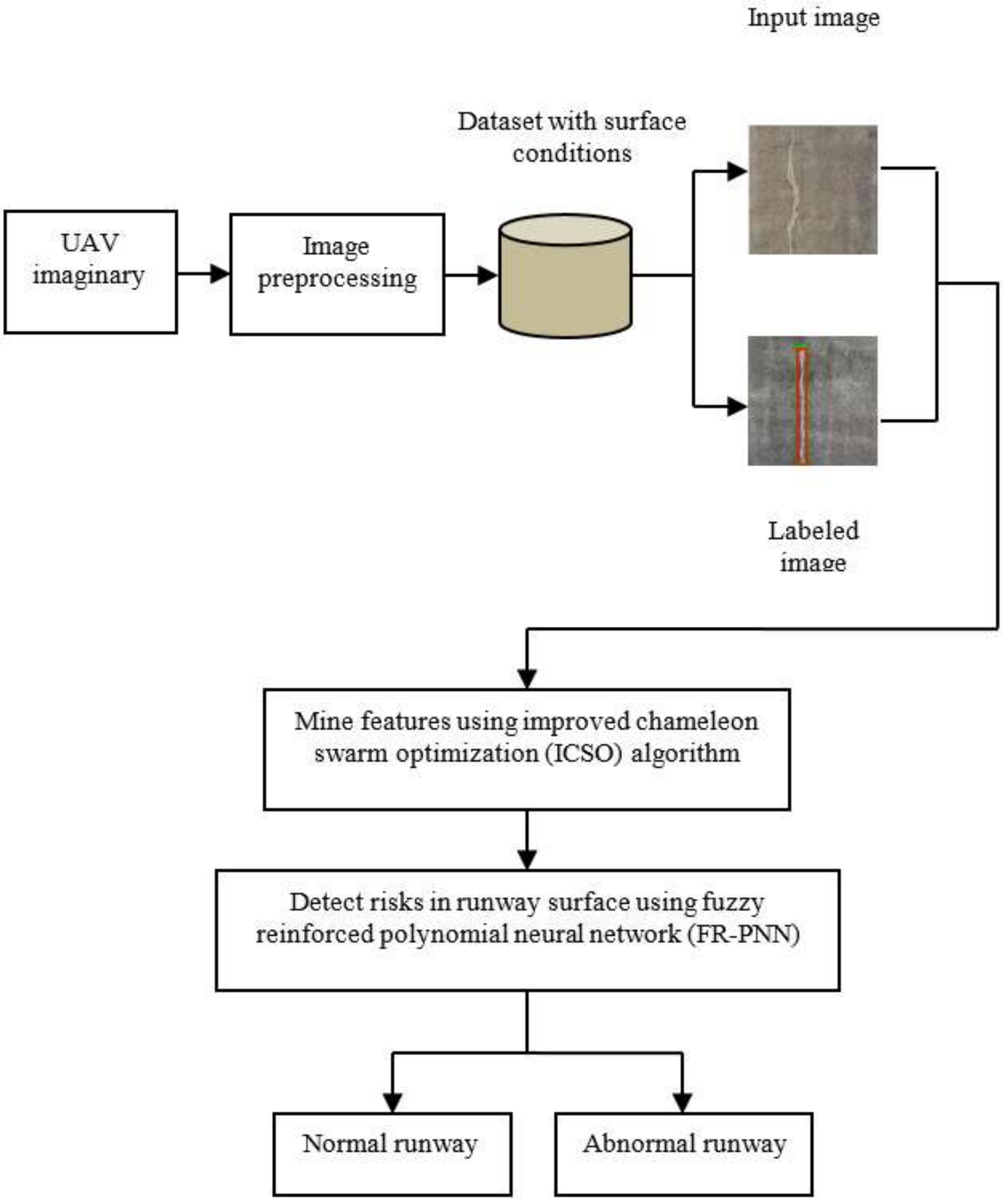

Figure 1. *Proposed real-time automatic monitoring system for runway risk detection*

3.1 Mine runway surface characteristics using ICSO algorithm

In our proposal, we propose to use improved chameleon swarm optimization (ICSO) for time-series analysis within a video mining framework collected from UAV-based real-time videos for runway surface characteristics. In fact, ICSO is a metaheuristic optimization approach that mimics the social behaviour of chameleons where parameters are varied adaptively by exploring the dynamic search space. By employing the ICSO algorithm for runway surface characterization, we aim to accurately capture the diverse attributes of the runway, including texture, roughness, moisture levels, and other relevant features. It enables us to create a comprehensive representation of the runway's condition over time, which is crucial for assessing its safety and suitability for aircraft operations. For a d-layered search space, every chameleon addresses an answer for the issue, so in the event that we call n competitor arrangements, we can characterize a n×d-layered two-layered y-lattice as the chameleon populace. We characterize it as h vector as follows.

$$q_s^h = \left[q_{s,1}^h, q_{s,2}^h, \ldots q_{s,c}^h\right] \tag{1}$$

where h= 1, 2, 3. . , b, and s are valid iterations $q_{s,c}^h$ specifying the position in the dth dimension. A numerical model for enhancing the way of behaving and headway of chameleons while looking for food can be introduced as follows.

$$q_{s+1}^{h,g} = \begin{cases} q_s^{h,g} + x_1\left(X_s^{h,g} - J_s^g\right)R_2 + x_2\left(J_s^g - X_s^{h,g}\right) & R_1 R_h \geq X_x \\ q_s^{h,g} + \mu\left(U^g - L^g\right)R_3 + L_n^g)\,\mathrm{sgn}\left(Rand - 0.5\right) & R_h < X_x \end{cases} \tag{2}$$

Here, is the new place of the h-th chameleon in the g-th aspect of the emphasis step. . addresses the best position involved by the jth size chameleon in the tth emphasis circle. addresses the worldwide best situation in the gth aspect arrived at by any chameleon in the sth emphasis. also, , two positive numbers control the strength of the test, , and , similarly dispersed arbitrary numbers somewhere in the range of 0 and 1. The , a uniform irregular number filed from 0 to 1. Sgn (rand - 0.5) influences the course of the hunt, can be either 1 or −1. μ is characterized as the iterative minimization capability of chameleons that quit going after and hunting when they are nearest to prey.

$$V_{s+1}^{h,g} = \omega V_s^{h,g} + d_1\left(J_s^g - q_s^{h,g}\right)R_1 + d_2\left(X_s^{h,g} - q_s^{h,g}\right)R_2 \tag{3}$$

where $V_{s+1}^{h,g}$ addresses the new speed of the chameleon in j. In cycle, size s + 1 addresses the ongoing rate of $V_s^{h,g}$. $\omega V_s^{h,g}$ addresses the ongoing place of the chameleon in the s-th aspect. $X_s^{h,g}$ is the ongoing chameleon's most popular position and is the most popular circular position at any point known to chameleons, $X_s^{h,g}$ is the ongoing chameleon's most popular position and is the best worldwide position at any point known to chameleons, and are the two positive constants controlling the impact of and falls while chameleon's tongue, and are two arbitrary numbers, circulated in the reach 0 to 1 and ω is the idleness gauge.

The communicated in the prey a piece of the chameleons addresses the place of the chameleons in the subsequent cycle. In the event that we add the change referenced above to this part, the turn grids on the applicable hub are communicated with R.

$$V = r\left(\Phi, q_s^{h,g}\right) \tag{4}$$

Here the turn network in V is addressed and characterized as a numerical model as follows.

$$\Phi = R\,\mathrm{sgn}\ (rand - 0.5) \times 180 \tag{5}$$

where R is an irregular number produced in the reach 0 to 1. The weight coefficients (−2) of the estimation capabilities are likewise remembered for the goal capability matches as an item. The goal capability pair adjusted from the power model is characterized as follows.

$$of_{11} = \sum_{h=1}^{B}\left(\frac{wd_1}{directivity_h}\right)^2 \tag{6}$$

$$of_{12} = \sum_{h=1}^{B}\left(\frac{wd_2}{-T11_h}\right)^2 \tag{7}$$

Adjusted from the remarkable model, the goal capability pair is characterized as follows:

$$of_{21} = \sum_{h=1}^{B} Wd_1 * E^{-directivity_h} \tag{8}$$

$$of_{22} = \sum_{h=1}^{B} Wd_2 * E^{T11_h} \tag{9}$$

The sets of goal capabilities adjusted from the Fourier model is characterized as follows:

$$of_{31} = \sum_{h=1}^{B} Wd_1 * \cos(directivity_h) \tag{10}$$

$$of_{32} = \sum_{h=1}^{B} Wd_2 * \cos(T11_h) \tag{11}$$

where h= 1, 2, . . . , 4 each addresses a reverberation recurrence. Notwithstanding every one of these, 2 different expense capabilities have been characterized. The first of these is acquired by gathering the 2 decided objective capability matches inside itself and is characterized as follows.

$$\cos s_1 = of_{g1} + of_{g2} g = 1, 2, 3 \tag{12}$$

The subsequent expense capability is characterized as continues to look at the goal capabilities on a typical premise.

$$\cos s_2 = \sum_{h=1}^{B} \frac{Wd_1}{directivity_h} + \frac{Wd_2}{-T11_h}, h = 1, 2, ...4 \tag{13}$$

The integration of the ICSO algorithm within our time-series analysis framework provides a robust and sound process for the extraction of runway surface characteristics from live video streams. This enables us to infer useful information regarding the runway's state and ultimately contribute to enhanced aviation safety and operational effectiveness.

3.2 Detect risks in runway surface characteristics

In our methodology, we employ the fuzzy reinforced polynomial neural network (FR-PNN) to efficiently identify risks related to runway surface features. The FR-PNN is an advanced computational model that integrates aspects of fuzzy logic and neural networks to process complex and uncertain patterns of data. The FR-PNN works by applying a set of fuzzy rules to understand the input data, which is inherently uncertain and can contain imprecise information. These fuzzy rules enable the FR-PNN to capture the intricate relationships between various runway surface features and the corresponding risks, considering the inherent uncertainties and variability in the data. The FR-PNN also employs polynomial neural network architectures, which offer the ability to capture nonlinear relationships and interactions between various input features. This allows the model to learn efficiently from the data and make accurate predictions about the presence of risks on the runway surface. The proposed FRPNs that comprise of estimate part (AP) and remuneration part (CP) emerge as original HPs. FRPNNs are basically summed up polynomial brain network design with HPs. Straight model is for the most part acknowledged by utilizing the information come from dataset for predication at delays h, where . M straight AR model can be communicated as follows.

$$I_h = c_1^h p_{s-1} + c_2^h p_{s-2} + ...c_x^h p_{s-x} + \xi_s^h \quad (14)$$

where I_h signifies the result of AR, $c_1^h, c_2^h....c_x^h$ address coefficients of AR, ξ_s^h and represents the lingering of AR. For accommodation, the contributions at the ongoing time t of nonlinear model are registered in light of the past assessment blunders $\{E_{s-1}, E_{s-2}, ...E_{s-a}\}$, where

$$E_s = p_s - \frac{\sum_{h=1}^{d} z_h (Ilh - \xi_s^h)}{\sum_{h=1}^{d} z_h} \quad (15)$$

Here c addresses the quantity of neurons of nonlinear models, wi indicates the ith weight of past assessment mistake. The Gaussian capability is $\varphi(p)$ portrayed as follows:

$$\varphi(p) = Exp\left(\frac{-1}{2}\left(\frac{p-\mu}{\sigma}\right)^2\right) \quad (16)$$

where μ ,, and uncommon the modular and spread upsides of the capability. Given $s = \frac{p-\mu}{\sigma}$,, a Mexican cap wavelet capability is $\Psi(s)$ communicated in the accompanying manner:

$$\Psi(s) = \frac{1}{\sqrt{|m|}}(1-2s^2)\exp\left(\frac{-s^2}{2}\right) \quad (17)$$

Where an is the boundary of the wavelet brain organization .According to the viewpoint of capability estimation, fluffy rule based models partitioned into non-added substance rule models and added substance rule models. TSK fluffy models can be viewed as a bunch of fluffy principles communicated as follows.

$$r^g : if\ p\ is\ M\ and\ q\ is\ N\ then\ w_g = F_g(p,q) \quad (18)$$

where r^g addresses the g-th fluffy rule of fluffy models, M and N are fluffy sets in the reason part, $w_g = F_g(p,q)$ and is numeric capability.

In many cases, $F_g(p,q)$ is a linear function of the input variables. The output $F(p_1, p_2, ...p_i)$ of the polynomial neural networks is described as follows.

$$F(p_1,p_2,p_3) = c_0 + \sum_{h=1}^{i} c_h p_h + \sum_{h=1}^{i}\sum_{h=1}^{i} c_{h,g} p_h p_g + \sum_{h=1}^{i}\sum_{g=1}^{i} \times \sum_{K=1}^{i} c_{hgK} p_h p_g p_K + ... \quad (19)$$

where c_0, c_i, $c_{h,g}$, c_{hgK} are polynomial coefficients. The FR-PNN comprises of two sections, specifically AP and CP. $P(p_{s-1}, p_{s-2}, p_{s-i})$ Here is the first information coming from the preparation information and testing information.

The estimate part is acknowledged by utilizing straight neurons. Expect that for the info $P(p_{s-1}, p_{s-2}, p_{s-i})$ information the result of the AP can be determined by a direct capability communicated as

$$l = c_0 + c_1 p_{s-1} + c_2 p_{s-1} + ... + c_x p_{s-x} \quad (20)$$

where L signifies the result of AP while c_0, c_i, $c_{h,g}$, c_{hgK}, are its coefficients. The remuneration part comprises of three units, specifically info, reason, and outcome unit. Regarding the information unit, the data sources are connected with the result of the AP. the contributions at the ongoing time t are registered in view of the past assessment blunders $\{E_{s-1}, E_{s-2}, E_{s-i}\}$, , where

$$E_s = p_s - \frac{\sum_{h=1}^{d} z_h I_i}{\sum_{h=1}^{d} z_h} \quad (21)$$

Regarding the reason unit, it is developed in light of chosen input factors utilizing fluffy parcel acknowledged by fluffy c-implies (FCM) bunching technique. Concerning the outcome unit, there exists three sources of info: $e = (E_{s-1}, E_{s-2}, E_{s-i})$, μ_g and σ_g. The initial two boundaries and . can be gotten from the reason unit, while the vector comes from the information unit. In the plan of the outcome unit, two sorts of nonlinear capabilities can be utilized. Spiral Premise Capabilities (Gaussian capability) can be taken on as the acknowledgment of the enrollment capability of the secret neurons. For this situation, the outflow of RN capability peruses as follows:

$$B_g = Exp\left(\frac{-1}{2}\left(\frac{e-\mu_g}{\sigma_g}\right)^2\right) \quad (22)$$

where B_g means the Gaussian capability, μ_g and σ_g The represent the particular place (mean) and spread of B_g, individually. Wavelet based nonlinear capabilities are utilized as the participation capability. For this situation, the result of the WN capability is shaped as:

$$B_g = \frac{1}{\sqrt{|m|}}\left(1 - 2\left(\frac{e-\mu_g}{\sigma_g}\right)^2\right)\exp\left(-\frac{(e-\mu_g)^2}{2\sigma_g^2}\right) \quad (23)$$

where m is the boundaries of the wavelet brain organization, μ_g and σ_g represent the separate place (mean) and spread, individually. Concerning the result unit, the result carries out a weighted amount of the result coming from stowed away layer. An overall CP is communicated as the accompanying fluffy guidelines:

$$r^h : if\ p\, is\, in\ cluster\ M_h\ then\ \hat{w}_h = \sum_{h=1}^{d} z_h B_h(p) \quad (24)$$

where r^h the g-th fluffy rule, M_h is the g-th bunch, d is the quantity of groups (fluffy standards), $\hat{w}_h$ is a weighted amount of the result of the h-th capability, and z_h is the enrollment of the h-th fluffy rule registered by FCM.

4. Results and Discussions

In this study, we present the findings and analysis of our proposed monitoring system alongside existing systems using test video datasets sourced from Bechyne military airport in southern Bohemia. Our design of the ICSO+FR-PNN system is conducted in Matlab, a programming language and numeric computing environment. We compare the performance of our proposed ICSO+FR-PNN system with several existing systems, including R-CNN, Faster R-CNN, SSD, YOLO9000, YOLOv2, YOLOv3, YOLOv4, YOLOv5, and YOLOv6. The comparison is based on various metrics such as accuracy, precision, sensitivity, specificity, and F-measure, allowing for a comprehensive evaluation of performance across different criteria.

4.1 Dataset description

The previous military air terminal Bechyne, arranged in southern Bohemia, Czech Republic, was picked as the essential hotspot for gathering picture information for the pain data set. The runway made out of cement, ranges 2400 meters long and 60 meters in width. Table 1 describes the dataset description. Following its closure for air traffic in 1993, including the cessation of regular maintenance, the airport became conducive to the gradual development of distresses. Unlike operational airports with established continuous maintenance systems, distress occurrences at Bechyne were more prevalent, making it an ideal candidate for generating the image database. For UAV flights, airspace leeway was gotten through the tactical part of the airspace the board cell (AMC) of the Czech Republic, and warnings were scattered by means of Notice to Pilot (NOTAM). The held airspace block enveloped a rectangular region estimating 2400 meters long and 450 meters in width, with vertical expansions to 91 meters (300 feet) over the ground level (AGL), consolidating the runway, runway framework, and unpaved regions. The runway was partitioned into four segments, with each part including a set number of pictures: the principal area had 383 pictures, the second had 391, the third had 393, and the fourth had 394. These pictures went through a progression of handling steps. At first, picture arrangement was performed to make a meager point cloud, with settings adapted to low exactness, conventional pre-choice empowered, central issue and tie point limits set, and versatile camera model fitting enacted. Consequently, the runway orthomosaic from the first to the third segments, produced utilizing Agisoft Metashape, was isolated into 224×224 picture blocks. Each block was classified as certain (containing a break) or negative (no break). Positive blocks highlighting longitudinal breaks went through expansion, including revolution by 90 degrees, and flat and vertical flipping, to grow the picture data set. Thusly, the dataset involved 3279 pictures, each containing at least one cross over breaks. The test tests from dataset are displayed in Figure 2.

Table 1. *Summary of dataset*

Class	Normal runway	Abnormal runway	Total samples
Training	1500	1000	2500
Testing	500	293	793
Total samples	2000	1293	3293

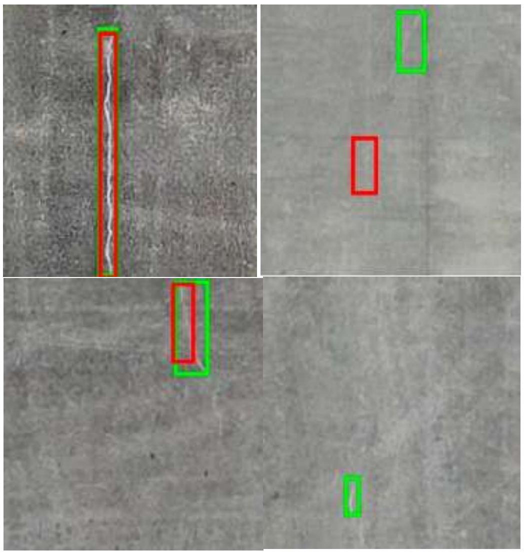

Figure 2. *Test samples from dataset*

4.2 Detection accuracy analysis

The table 2 presents the accuracy comparison of various systems for runway monitoring across different epochs. Initially, the R-CNN system starts with an accuracy of 63.705% at epoch 20 and gradually increases to 64.195% by epoch 100. Similarly, the Faster R-CNN system exhibits a slight improvement from 67.364% to 67.854% over the same epochs. Moving forward, the SSD system shows a more noticeable increase in accuracy from 71.023% to 71.513%. The YOLO series, including YOLO9000, YOLOv2, YOLOv3, YOLOv4, YOLOv5, and YOLOv6, consistently show significant improvements in accuracy with each epoch. For instance, YOLOv6 achieves the highest accuracy of 92.976% at epoch 20, steadily rising to 93.466% by epoch 100. In comparison, the proposed ICSO+FR-PNN system surpasses all other systems in terms of accuracy across all epochs. It begins with an impressive accuracy of 96.635% at epoch 20 and continues to improve steadily, reaching 97.125% by epoch 100. This represents a considerable advancement over existing techniques, demonstrating the effectiveness of the integrated approach utilizing the ICSO algorithm for feature mining and the FR-PNN model for risk detection. Overall, the results from Figure 3 highlight the superior performance of the proposed ICSO+FR-PNN system, shows a significant increase in accuracy compared to existing systems.

4.3 Precision analysis

Table 3 presents the precision comparison of various systems for runway monitoring across different epochs. Initially, the R-CNN system exhibits a precision of 62.034% at epoch 20, which gradually increases to 62.811% by epoch 100. Similarly, the Faster R-CNN system demonstrates incremental precision improvements from 65.723% to 66.500% over the same epochs. The SSD system follows a similar trend, with precision rising from 69.412% to 70.189%. Moving on to the YOLO series, including YOLO9000, YOLOv2, YOLOv3, YOLOv4, YOLOv5, and YOLOv6, each system consistently improves precision with each epoch. For instance, YOLOv6 achieves a precision of 91.546% at epoch 20, steadily increasing to 92.323% by epoch 100. In comparison, the proposed ICSO+FR-PNN system outperforms all other systems in terms of precision across all epochs. It starts with a precision of 95.235% at epoch 20 and continues to improve steadily, reaching 96.012% by epoch 100. This signifies a significant percentage-wise increase in precision compared to existing techniques, highlighting the effectiveness of the integrated approach utilizing the ICSO algorithm for feature mining and the FR-PNN model for risk detection. Overall, the results from Figure 4 demonstrate the superior precision achieved by the proposed ICSO+FR-PNN system, indicating its potential for enhancing runway monitoring accuracy and ensuring the safety of aircraft operations.

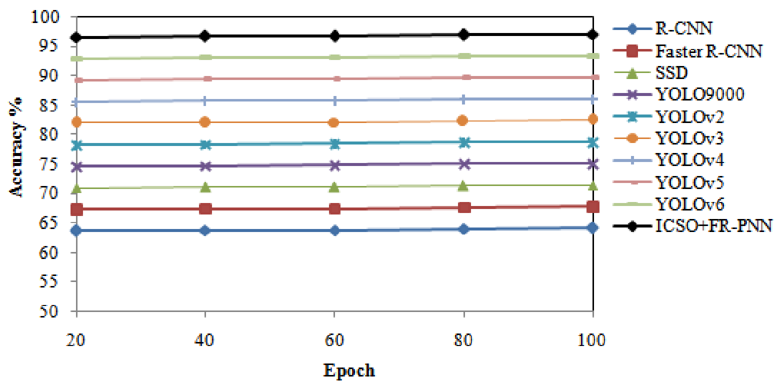

Figure 3. *Accuracy results of various systems for runway monitoring*

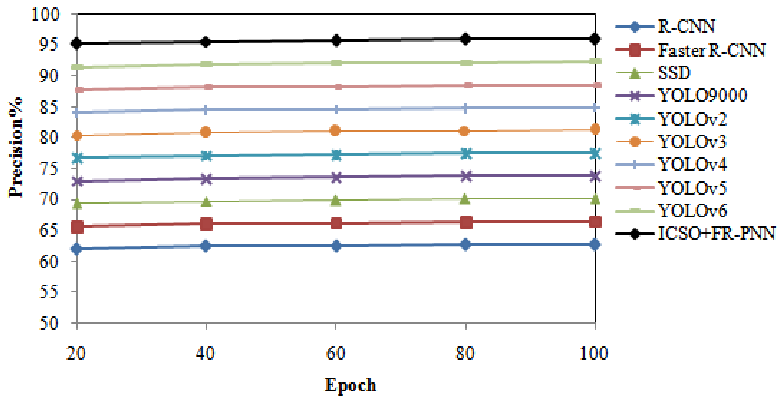

Figure 4. *Precision results of various systems for runway monitoring*

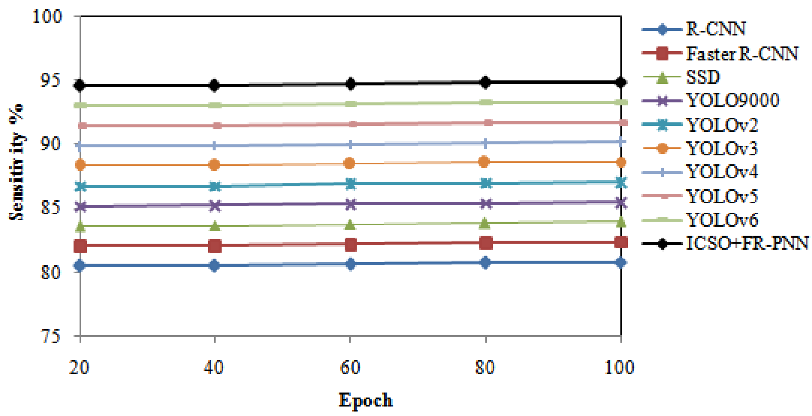

Figure 5*. Sensitivity results of various systems for runway monitoring*

Table 2 *Accuracy comparison of various systems for runway monitoring*

Runway monitoring system	Epoch				
	20	40	60	80	100
R-CNN	63.705	63.824	63.859	64.091	64.195
Faster R-CNN	67.364	67.483	67.518	67.750	67.854
SSD	71.023	71.142	71.177	71.409	71.513
YOLO9000	74.682	74.801	74.836	75.068	75.172
YOLOv2	78.341	78.460	78.495	78.727	78.831
YOLOv3	81.999	82.118	82.153	82.385	82.489
YOLOv4	85.658	85.777	85.812	86.044	86.148
YOLOv5	89.317	89.436	89.471	89.703	89.807
YOLOv6	92.976	93.095	93.130	93.362	93.466
ICSO+FR-PNN	96.635	96.754	96.789	97.021	97.125

Table 3. *Precision comparison of various systems for runway monitoring*

Runway monitoring system	Epoch				
	20	40	60	80	100
R-CNN	62.034	62.441	62.583	62.785	62.811
Faster R-CNN	65.723	66.130	66.272	66.474	66.500
SSD	69.412	69.819	69.961	70.163	70.189
YOLO9000	73.101	73.508	73.650	73.852	73.878
YOLOv2	76.790	77.197	77.339	77.541	77.567
YOLOv3	80.479	80.886	81.028	81.230	81.256
YOLOv4	84.168	84.575	84.717	84.919	84.945
YOLOv5	87.857	88.264	88.406	88.608	88.634
YOLOv6	91.546	91.953	92.095	92.297	92.323
ICSO+FR-PNN	95.235	95.642	95.784	95.986	96.012

Table 4. *Sensitivity comparison of various systems for runway monitoring*

Runway monitoring system	Epoch				
	20	40	60	80	100
R-CNN	80.515	80.545	80.678	80.758	80.831
Faster R-CNN	82.078	82.108	82.241	82.321	82.394
SSD	83.641	83.671	83.804	83.884	83.957
YOLO9000	85.204	85.234	85.367	85.447	85.520
YOLOv2	86.767	86.797	86.930	87.010	87.083
YOLOv3	88.330	88.360	88.493	88.573	88.646
YOLOv4	89.893	89.923	90.056	90.136	90.209
YOLOv5	91.456	91.486	91.619	91.699	91.772
YOLOv6	93.019	93.049	93.182	93.262	93.335
ICSO+FR-PNN	94.582	94.612	94.745	94.825	94.898

Table 5. *Specificity comparison of various systems for runway monitoring*

Runway monitoring system	Epoch				
	20	40	60	80	100
R-CNN	70.524	70.558	70.638	70.744	70.858
Faster R-CNN	73.084	73.118	73.198	73.304	73.418
SSD	75.644	75.678	75.758	75.864	75.978
YOLO9000	78.204	78.238	78.318	78.424	78.538
YOLOv2	80.764	80.798	80.878	80.984	81.098
YOLOv3	83.324	83.358	83.438	83.544	83.658
YOLOv4	85.884	85.918	85.998	86.104	86.218
YOLOv5	88.444	88.478	88.558	88.664	88.778
YOLOv6	91.004	91.038	91.118	91.224	91.338
ICSO+FR-PNN	93.564	93.598	93.678	93.784	93.898

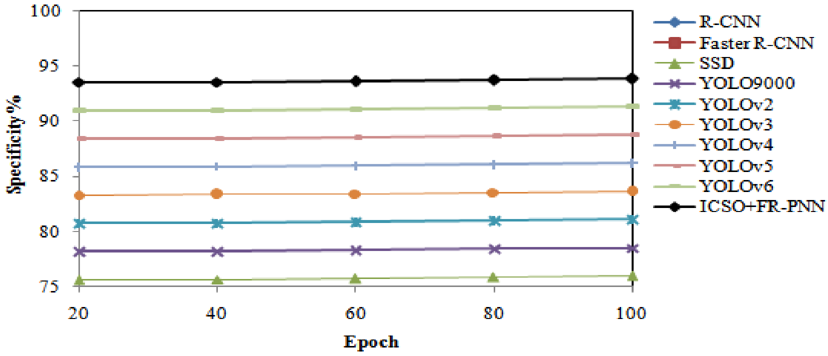

Figure 6. *Specificity results of various systems for runway monitoring*

Table 6*. F-measure comparison of various systems for runway monitoring*

Runway monitoring system	Epoch				
	20	40	60	80	100
R-CNN	70.077	70.347	70.488	70.646	70.691
Faster R-CNN	72.996	73.258	73.398	73.554	73.599
SSD	75.865	76.120	76.259	76.412	76.458
YOLO9000	78.690	78.938	79.077	79.228	79.274
YOLOv2	81.474	81.716	81.855	82.003	82.050
YOLOv3	84.222	84.458	84.596	84.743	84.790
YOLOv4	86.936	87.167	87.305	87.450	87.498
YOLOv5	89.620	89.846	89.984	90.127	90.176
YOLOv6	92.277	92.498	92.635	92.777	92.826
ICSO+FR-PNN	94.907	95.124	95.262	95.402	95.452

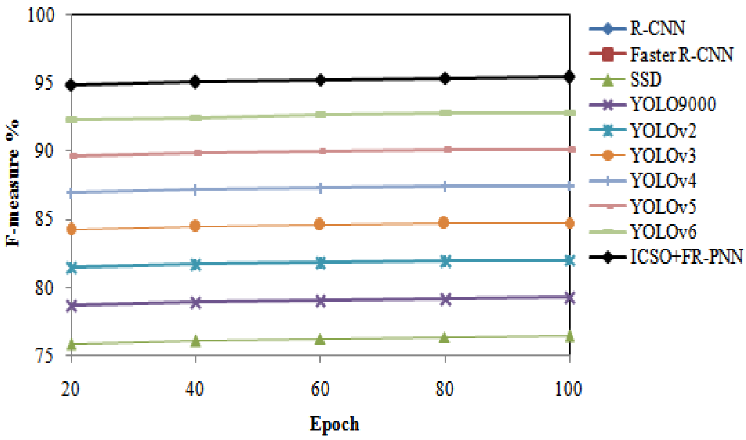

Figure 7. *F-measure results of various systems for runway monitoring*

4.4 Sensitivity analysis

Table 4 presents a sensitivity comparison of different systems for runway monitoring over different epochs. The R-CNN system begins with a sensitivity of 80.515% at epoch 20, with slight variations before reaching 80.831% at epoch 100. Likewise, the Faster R-CNN system shows a gradual rise in sensitivity from 82.078% to 82.394% over the epochs. The SSD system shows a steady increase in sensitivity, rising from 83.641% to 83.957% over the epochs. Proceeding to the YOLO series, each system shows a steady rise in sensitivity with each epoch. For example, YOLOv6 reaches a sensitivity of 93.019% at epoch 20, steadily rising to 93.335% at epoch 100. In contrast, the proposed ICSO+FR-PNN system consistently performs better than other systems in terms of sensitivity at all epochs. It begins with a sensitivity of 94.582% at epoch 20 and continues on an upward trend, reaching 94.898% at epoch 100. This is a significant rise in sensitivity over existing methods, highlighting the efficacy of the integrated approach using the ICSO algorithm and FR-PNN model. Overall, the results of Figure 5 emphasize the higher sensitivity of the proposed ICSO+FR-

PNN system, reflecting its potential for improving the detection performance of runway monitoring systems and ensuring the safety of aircraft operations.

4.5 Specificity analysis

Table 5 presents a specificity comparison of various systems for runway monitoring across different epochs. Starting with the R-CNN system, it begins with a specificity of 70.524% at epoch 20, gradually increasing to 70.858% by epoch 100. Similarly, the Faster R-CNN system shows a consistent rise in specificity, progressing from 73.084% to 73.418% across the epochs. Moving to the SSD system, there is a steady increase in specificity, with values ranging from 75.644% to 75.978% across the epochs. The YOLO series also demonstrates a notable increase in specificity with each epoch, with YOLOv6 reaching 91.004% at epoch 20 and climbing to 91.338% by epoch 100. In comparison, our ICSO+FR-PNN system consistently outperforms other systems in terms of specificity across all epochs. It starts with a specificity of 93.564% at epoch 20 and maintains an upward trend, reaching 93.898% by epoch 100. This represents a significant increase in specificity compared to existing techniques, highlighting the effectiveness of the integrated approach utilizing the ICSO algorithm and FR-PNN model. Overall, the results from Figure 6 underscore the superior specificity achieved by the proposed ICSO+FR-PNN system, indicating its potential for enhancing the accuracy of runway monitoring systems and reducing false alarms, thereby contributing to improved aviation safety.

4.6 F-measure analysis

Table 6 presents the F-measure comparison of various systems for runway monitoring across different epochs. Starting with the R-CNN system, it begins with an F-measure of 70.077% at epoch 20, gradually increasing to 70.691% by epoch 100. Similarly, the Faster R-CNN system shows a consistent rise in F-measure, progressing from 72.996% to 73.599% across the epochs. Moving to the SSD system, there is a steady increase in F-measure, with values ranging from 75.865% to 76.458% across the epochs. The YOLO series also demonstrates a notable increase in F-measure with each epoch, with YOLOv6 reaching 92.277% at epoch 20 and climbing to 92.826% by epoch 100. In comparison, our ICSO+FR-PNN system consistently outperforms other systems in terms of F-measure across all epochs. It starts with an F-measure of 94.907% at epoch 20 and maintains an upward trend, reaching 95.452% by epoch 100. This represents a significant percentage-wise increase in F-measure compared to existing techniques, highlighting the effectiveness of the integrated approach utilizing the ICSO algorithm and FR-PNN model. Overall, the results from Figure 7 underscore the superior F-measure achieved by the proposed ICSO+FR-PNN system, indicating its potential for enhancing the overall performance and reliability of runway monitoring systems, thereby contributing to improved aviation safety.

5. Conclusion

Our study introduces a real-time automatic monitoring system designed for enhancing runway safety through video analysis. Leveraging a time-series analysis methodology, we employ the improved chameleon swarm optimization (ICSO) algorithm to extract essential runway surface characteristics from live video data captured by UAVs. Subsequently, we utilize the fuzzy reinforced polynomial neural network (FR-PNN) to identify potential risks associated with runway surface conditions, thereby facilitating automated monitoring to bolster the safety of aircraft landings. To evaluate the effectiveness of our proposed system, we conduct validation tests using real-time videos acquired from Bechyne military airport in southern Bohemia. Our findings reveal that the ICSO+FR-PNN model achieves an impressive average accuracy of approximately 96.865%. This surpasses the maximum average accuracy attained by existing techniques, which stands at approximately 93.206%. Consequently, our approach demonstrates a significant improvement of approximately 3.93% over current methods, highlighting its superior efficacy in accurately monitoring runways for potential risks and hazards. Video Analysis is used in litrrature for some applications [32-34].

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
- **Acknowledgement:** The authors declare that they have nobody or no-company to acknowledge.
- **Author contributions:** The authors declare that they have equal right on this paper.

- **Funding information:** The authors declare that there is no funding to be acknowledged.
- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

References

[1] Vorobyeva, O., Bartok, J., Šišan, P., Nechaj, P., Gera, M., Kelemen, M., ...&Gaál, L. (2020). Assessing the contribution of data mining methods to avoid aircraft run-off from the runway to increase the safety and reduce the negative environmental impacts. *International journal of environmental research and public health*, 17(3), 796.

[2] Gradolewski, D., Dziak, D., Kaniecki, D., Jaworski, A., Skakuj, M., &Kulesza, W. J. (2021). A runway safety system based on vertically oriented stereovision.*Sensors*, 21(4), 1464.

[3] Bongo, M., &Seva, R. (2022). Effect of Fatigue in Air Traffic Controllers' Workload, Situation Awareness, and Control Strategy. *The International Journal of Aerospace Psychology*, 32(1), 1-23.

[4] Zhang, J., Zou, X., Wu, Q., Xie, F., & Liu, W. (2020). Empirical study of airport geofencing for unmanned aircraft operation based on flight track distribution. *Transportation Research Part C: Emerging Technologies*, 121, 102881.

[5] Koroniotis, N., Moustafa, N., Schiliro, F., Gauravaram, P., &Janicke, H. (2020). A holistic review of cybersecurity and reliability perspectives in smart airports. *IEEE Access*, 8, 209802-209834.

[6] Ruskin, K. J., Corvin, C., Rice, S., Richards, G., Winter, S. R., & Ruskin, A. C. (2021). Alarms, alerts, and warnings in air traffic control: an analysis of reports from the Aviation Safety Reporting System. *Transportation research interdisciplinary perspectives*, 12, 100502.

[7] Malygin, I., Borodina, O., &Komashinsky, V. (2020). Decision support systems for ensuring safety of overland traffic at major airports.*Transportation research procedia*, 50, 422-429.

[8] Khadonova, S. V., Ufimtsev, A. V., &Dymkova, S. S. (2020, October). "Digital Smart Airport" System Based on Innovative Navigation and Information Technologies. In *2020 International Conference on Engineering Management of Communication and Technology (EMCTECH)* (pp. 1-6).IEEE.

[9] Pestana, G., Reis, P., & da Silva, T. R. (2021). Smart Surveillance of Runway Conditions. In Intelligent Transport Systems, From Research and Development to the Market Uptake: 4th *EAI International Conference, INTSYS 2020, Virtual Event, December 3, 2020, Proceedings* 4 (pp. 252-270). Springer International Publishing.

[10] Pramanik, P. K. D., Mukherjee, B., Pal, S., Upadhyaya, B. K., &Dutta, S. (2020). Ubiquitous manufacturing in the age of industry 4.0: A state-of-the-art primer. A Roadmap to Industry 4.0: Smart Production, *Sharp Business and Sustainable Development*, 73-112.

[11] Korkmaz, H., Filazoglu, E., &Ates, S. S. (2023). Enhancing airport apron safety through intelligent transportation systems: Proposed FEDA model.*Safety science*, 164, 106184.

[12] Yousefi, Y., Karballaeezadeh, N., Moazami, D., SanaeiZahed, A., Mohammadzadeh S, D., &Mosavi, A. (2020). Improving aviation safety through modeling accident risk assessment of runway.*International journal of environmental research and public health*, 17(17), 6085.

[13] Motlagh, N.H., Kortoçi, P., Su, X., Lovén, L., Hoel, H.K., Haugsvær, S.B., Srivastava, V., Gulbrandsen, C.F., Nurmi, P., & Tarkoma, S. (2023). Unmanned Aerial Vehicles for Air Pollution Monitoring: A Survey. *IEEE Internet of Things Journal*, 10, 21687-21704.

[14] Iqbal, M. J., Iqbal, M. M., Ahmad, I., Alassafi, M. O., Alfakeeh, A. S., &Alhomoud, A. (2021). Real-time surveillance using deep learning. *Security and Communication Networks*, 2021, 1-17.

[15] Esteva, A., Chou, K., Yeung, S., Naik, N., Madani, A., Mottaghi, A., ...&Socher, R. (2021). Deep learning-enabled medical computer vision. *NPJ digital medicine*, 4(1), 5.

[16] Shin, W., Bu, S. J., & Cho, S. B. (2020). 3D-convolutional neural network with generative adversarial network and autoencoder for robust anomaly detection in video surveillance. *International Journal of Neural Systems*, 30(06), 2050034.

[17] Puranik, T. G., Rodriguez, N., &Mavris, D. N. (2020). Towards online prediction of safety-critical landing metrics in aviation using supervised machine learning. *Transportation Research Part C: Emerging Technologies*, 120, 102819.

[18] Van Phat, T., Alam, S., Lilith, N., Tran, P. N., &Binh, N. T. (2021, July). Deep4air: A novel deep learning framework for airport airside surveillance. In 2021 *IEEE International Conference on Multimedia & Expo Workshops (ICMEW)* (pp. 1-6).IEEE.

[19] Odisho, E. V., Truong, D., &Joslin, R. E. (2022). Applying machine learning to enhance runway safety through runway excursion risk mitigation. *Journal of Aerospace Information Systems*, 19(2), 98-112.

[20] Xiang, Z., Yan, J., &Demir, I. (2020). A rainfall-runoff model with LSTM-based sequence-to-sequence learning. *Water resources research*, 56(1), e2019WR025326.

[21] Li, X., Shang, J., Zheng, L., Wang, Q., Liu, D., Liu, X., ...& Sun, H. (2023). IMTCN: An Interpretable Flight Safety Analysis and Prediction Model Based on Multi-Scale Temporal Convolutional Networks. *IEEE Transactions on Intelligent Transportation Systems.*

[22] Farhadmanesh, M., Marković, N., &Rashidi, A. (2023). Automated video-based air traffic surveillance system for counting general aviation

aircraft operations at non-towered airports. *Transportation research record*, 2677(3), 250-273..

[23] Sun, Z. (2023, February). Research on the Application of Convolutional Neural Network Based on the YOLO Algorithm in Airport Intelligent Monitoring. In 2023 3rd *Asia-Pacific Conference on Communications Technology and Computer Science (ACCTCS)* (pp. 103-108).IEEE.

[24] Jin, X., Peng, J., Jiao, X., & Hu, C. (2024, January). Construction and application of aircraft turnaround time research based on the video analysis platform. *In International Conference on Algorithm, Imaging Processing, and Machine Vision* (AIPMV 2023) (Vol. 12969, pp. 408-415). SPIE.

[25] N. Soriano, A. Negahban, S. GokhanOzden and O. Ashour, (2023). An Open Source Video Analytics Tool for Analyzing Learner Navigation in Immersive Simulated Environments, *2023 Annual Modeling and Simulation Conference (ANNSIM), Hamilton*, ON, Canada, pp. 472-483.

[26] Han, J., Ren, Y. F., Brighente, A., & Conti, M. (2024). RANGO: A Novel Deep Learning Approach to Detect Drones Disguising from Video Surveillance Systems. *ACM Transactions on Intelligent Systems and Technology*. 15(2);1 – 21 https://doi.org/10.1145/3641282

[27] Balasubramanian, M., Ramyadevi, K., &Geetha, R. (2023). Deep transfer learning based real time face mask detection system with computer vision. *Multimedia Tools and Applications*, 1-20.

[28] Thamilarasi V., Roselin. R., (2023). Application of Machine Learning in chest X-Ray images, *International book & River publisher series in computing and information science and Technology*, pp: 52-1.

[29] Ran, J., Wan, H., Tang, W., & Kang, W. (2023, October). A Deep Learning-Based Flight Turnaround Record System.In 2023 *International Annual Conference on Complex Systems and Intelligent Science (CSIS-IAC)* (pp. 896-903).IEEE.

[30] Li, C., Sun, R., & Pan, X. (2023). Takeoff runway overrun risk assessment in aviation safety based on human pilot behavioral characteristics from real flight data. *Safety science*, 158, 105992.

[31] Zhao, X. (2023, January). Design and Research of Airfield Navaid Lighting Monitoring System Based on Data Mining Algorithm. *In International Conference on Innovative Computing* (pp. 96-102). Singapore: Springer Nature Singapore.

[32] AY, S. (2024). Vehicle Detection And Vehicle Tracking Applications On Traffic Video Surveillance Systems: A systematic literature review. *International Journal of Computational and Experimental Science and Engineering*, 10(4). https://doi.org/10.22399/ijcesen.629

[33] S.P. Lalitha, & A. Murugan. (2024). Performance Analysis of Priority Generation System for Multimedia Video using ANFIS Classifier. *International Journal of Computational and Experimental Science and Engineering*, 10(4). https://doi.org/10.22399/ijcesen.707

[34] GÜNGÖRDÜ, G., & İMAMOĞLU, B. (2024). Occupational Health and Safety Risks in Aircraft Arresting Barrier Systems. *International Journal of Computational and Experimental Science and Engineering*, 10(4). https://doi.org/10.22399/ijcesen.748