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REAL-TIME MONITORING AND EARLY WARNING SYSTEM FOR UNMANNED AERIAL VEHICLE INTEGRATED WITH PIPELINE MONITORING USING DEEP LEARNING WITH YOLOV5

[1]Dr.A.Jayasudha, [2]V.Thamilarasi, [3]G.Sivaraman,[4]Dr. N.Kanya,

[1]Assistant Professor, SRM Arts and Science College, Kattankulathur, Tamil Nadu, India.

ORCID ID:0009-0007-2047-0885, jsudhaannamalai@gmail.com

[2]Assistant Professor, Sri Sarada College for Women (Autonomous), Salem, Tamilnadu, India.

ORCID ID:0000-0002-5866-0074, tamilomsiva@gmail.com,

[3] Assistant Professor, M.G.R College (Arts and Science), Hosur, Tamilnadu, India.

ORCID ID: 0009-0005-9342-2716, gsivaramanphd@gmail.com,

[4]Professor of Information Technology, Dr.M.G.R.Educational and Research Institute, chennai, Tamilnadu, India

ORCID ID:0000-0001-8549-6444, kanya.v@drmgrdu.ac.in

Abstract

Because they are the most popular way to transport hydrocarbons fluids, gases, and fossil fuels globally, pipelines are crucial to the oil and gas sector. Maintaining infrastructure stability and error-free output from these pipelines calls for constant monitoring. A reliable monitoring system that can identify small leaks that numerous sensors could miss is still desperately needed, despite the fact that pipeline monitoring has come a long way. The unmanned aerial vehicle's (UAV) capacity to collect extremely useful data has increased its applicability in a number of fields. Precise object tracking has been crucial for UAVs used for surveillance in the pipeline. Problems like occlusion and shifts in object representation are typical during UAV-based pipeline monitoring. It is difficult to keep track of the objects in this kind of environment. In this work, we proposed the real-time monitoring and early warning system for UAV integrated with pipeline monitoring using deep learning with YOLOv5. Firstly, we introduced the hybrid DenseNet with stochastic dual elemental algorithm for feature extraction and optimization which extracts more deep features from the gathered pipeline images and optimizes the feature to selects best of them. We then integrate YOLOv5 with deep recurrent neural network (improved YOLOv5) for pipeline threat events detection which ensures the real-time monitoring and early warning like cracks and leakages. To validate the performance of proposed and existing systems using the publicly available sources and the results show their effectiveness. The maximum detection accuracy is achieved by an improved YOLOv5 is 97.856% which is 12.92% higher than the existing state-of-art systems.

Keywords: UAV, pipeline monitoring, deep learning, improved YOLOv5, pipeline threats, cracks, leakages

1. Introduction

Recently, pipeline monitoring and inspection have deployed them [1]. Distribution pipes carry water, gas, and oil. Standard examination methods are difficult and time-consuming in vast, inaccessible, or distant places. Unmanned aerial vehicles (UAVs) may convey pipelines route assessments and inspections cheaply [2]. Energy, industrial and home utilities need pipelines. Pipeline damage could endanger public, financial, and ecological safety [3][4]. Thus, pipeline surveillance and early warning technologies that identify risks and vulnerabilities are crucial. Pipeline security is preemptive with UAV sensors, cameras, and communications [5]. UAVs can handle emergencies, crises, and inspections. UAVs respond rapidly to pipeline spills and breaches of security [6]. Integrating UAV technology to pipeline surveillance and safety devices protects key infrastructure from growing threats [7]. Since regular monitoring and threat identification tools are accessible, protecting pipeline infrastructure is difficult [8][9]. Operators may miss minor damage or sabotage in isolated pipeline networks over several hundred miles long. Security fences and CCTV systems react to potential threats [10].

Adequate security and surveillance are needed to protect pipelines from vandalism, sabotage, and terrorism [11]. Threat actors' shifting strategies and behaviors require new solutions that employ emerging technology and data insights. Threat actors evolve, thus this is necessary. Due to pipeline system size, complexity, and environmental and topographical variations, monitoring and early warning problems are difficult to manage [12]. Pipelines can be damaged by outside threats, operating dangers, catastrophic occurrences, and environmental difficulties. Pipeline inspections are needed to detect and fix rust, subsidence, which is tremors, and adverse weather conditions. Operators risk financial losses, regulatory violations, and reputation damage by doing so. Real-time monitoring systems allow operators extraordinary sight and situational awareness, thus improving pipeline safety and overall safety [13]. Technologies use sensors, cameras, and data networks for real-time analytics to discover, evaluate, and respond to threats and irregularities. This is done with several technologies. Acoustic detectors detect pipeline leaks and breaches by detecting unusual sound patterns [14]. This aids operators in problem identification and assessment. Infrared cameras detect pipeline right-of-way temperature abnormalities. Temperature anomalies may indicate device failure, corrosion, or unwanted activity. With the rise in Internet of Things devices and mobile networks, incorporating real-time monitoring technologies into pipeline infrastructure is easier [15]. Remote telemetry systems allow operators to monitor the pressure, flow rate, and temperatures from central control centers or mobile devices. Advanced analytics algorithms evaluate enormous sensor data in real time using machine learning and intelligence from computation [16].

Satellite imagery, drones, and UAVs have revolutionized pipeline inspection and surveillance [17]. These platforms allow operators to inspect pipelines, identify obstructions, and assess vegetation management tactics. UAVs with excellent cameras, LiDAR scanners, and gas detection sensors can inspect pipeline assets quickly and accurately [18]. Real-time monitoring technologies can help operating firms protect fossil fuels and the natural world for future generations by improving pipeline resiliency, dependability, and security. YOLOv5 is a highly advanced object detection method. It improves real-time picture identification and categorization over its predecessors [19]. YOLOv5, designed by computer vision professionals, contains several additions and optimizations to improve the precision of detection, speed, and efficiency. A unified design in YOLOv5 allows detection and classification in one neural network pass. In contrast, standard object detection methods use area suggestion networks and multiple phases processing pipelines. YOLOv5's deep CNN foundation is adhered to by convolutional layering and forecast heads, which recognize objects of interest in input images [20]. UAVs and drones monitoring pipeline safety and identifying threats can provide real-time aerial imagery for YOLOv5 to detect intruders, vehicles, and hazards. Its rapidity and accuracy make it ideal for dynamic situations requiring fast identification and reaction to protect critical infrastructure assets. YOLOv5 lets operators monitor and minimize pipeline risks in early alert and constant monitoring systems.

Based on the consideration, we developed the improved YOLOv5 for pipeline monitoring to detect crack and leakage. The main objective is to enhance the effectiveness, the real-time monitoring and early warning system for UAV images and deep learning with YOLOv5 for the pipeline monitoring. The following key contributions involved in the proposed work.

1. The hybrid DenseNet with stochastic dual elemental algorithm for feature extraction and optimization which extracts more deep features from the gathered pipeline images and optimizes the feature to selects best of them.
2. To integrate YOLOv5 with deep recurrent neural network (improved YOLOv5) for pipeline threat events detection which ensures the real-time monitoring and early warning like cracks and leakages.
3. To validate the performance of proposed and existing systems using the publicly available sources and the results show their effectiveness.

The rest of this paper is organized as follows. In Section 2, we present a thorough review of the existing literature concerning the pipeline monitoring to detect crack and leakage. Section 3 delves into the research methodologies and principles employed in this study, including the improved YOLOv5 for pipeline monitoring. Moving forward, Section 4 conducts comparative experiments 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 works

Yasmiine et al. 2023 [21] sate due to the proliferation of drones and their susceptibility for harmful use, this article exploits AI and cyber security loopholes to strengthen and safeguard aerial security and privacy. Anti-drone systems are essential for aerial safety against rogue drones, but they struggle with airborne recognition of targets and real-time detection without damage. Yolov7-based real-time multi-target detection model to quickly and effectively detect, recognize, and locate airborne targets. The model optimizes performance with the

CSP ResNeXt component, a transformation chunk with the C3TR care instrument, and a disconnected skull assembly using a diverse dataset with inherent prejudices and imbalances between targets. It provides a strong and efficient approach for real-time risk detection and abatement in the face of growing drone threats, improving airborne security and safety.

Aydin et al. 2023 [22] compared YOLOv5, one of the most recent forms of YOLO, to our drone discovery approach using YOLOv4. We tailored YOLOv5 to detect birds and drones using the same dataset and computer settings, improving parameters like rate of learning and momentum for accuracy. Data enhancement and pretreatment using transfer learning and MS COCO dataset weights addressed data shortages and overfitting. Improvements in precision, recall, F-1 score, and mAP over the prior model were notable, particularly a 21.57% rise in mAP. Use an NVIDIA Tesla T4 GPU, measured detection speed on DJI Phantom III and DJI Mavic Pro drone recordings, attaining all-out FPS values of 23.9 and 31.2 across various altitudes. Various YOLO versions, larger datasets, and various object detection techniques will be tested in the future. By adding classes like airplanes, we want to improve the model's capacity to distinguish comparable items in real life.

Usamentiaga et al. 2023 [23] introduce a semiautonomous pipeline inspection system using UAVs and infrared thermal imaging to ensure pipeline safety and reliability. The technology detects pipeline flaws and odd temperature patterns using automated flying and high-speed data collecting and advanced processing. It uses automated vision-based tracking and identification and deep learning algorithms for rigorous analysis and inspection from flight design to data collecting and processing. An active learning method improves inspection efficiency and efficacy. The approach is effective in industrial applications, especially in detecting insulation problems and product leaks that threaten pipeline integrity, according to extensive testing.

Bharathi et al. 2023 [24] introduce a bespoke YOLOv5-based actual time fire detection technique that analyzes video streams using deep learning. After training on a dataset of fire photos and testing on a separate verification set, the model detected flames in 0.02 seconds per frame, indicating enhanced real-time performance. The F1-score of 98 and accuracy rate of 98.3% outperformed other approaches. Moderate recall allows the system to detect even small fire items, perhaps preventing fire outbreaks and reducing damage and death. To improve fire detection and prevention, further research might improve the algorithm's precision and speed, expand the data used for training, and integrate the system with drones or robotics.

Chen et al. 2024 [25] found that remote communication oil and gas pipeline surface faults offer mainsecurity threats. MFL identification is a beneficial non-destructive testing tool for pipeline fault mapping, but typical data processing can reduce its accuracy and dependability. The hybrid method employs YOLOv5 and ViT computer vision techniques to accurately detect and classify pipeline issues. The model was trained and evaluated using a within the company empirical data from pull through testing with controlled pipeline faults such metal corrosion and geometrical irregularities. The study found that the cascaded method Classifies pipeline faults better than YOLOv5 while retaining the detection of defects precision. This

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new technology may reduce long-distance pipeline hazards by identifying and classifying issues.

Noise barriers reduce train noise while avoiding foreign objects from entering railroads, according to Cui et al. 2023 [26]. Noise barrier structural issues including rusting columns and masonry layers risk rail safety. Manual inspections are ineffective, subjective, and often miss external structural issues. This research proposes automatic inspection using UAV pictures and an FCN-based noise barriers defect detection system dubbed bypass connection YOLO detection network to address these challenges. Skip-connected feature structure (Simi-BiFPN) efficiently fuses scale layer features in SCYNet, improving computational efficiency. A unique Noise IoU loss function increases bounding box regression accuracy, while AutoFMix mixed data sample replenishment lowers overfitting and enhances detection. SCYNet exceeds other models in accuracy and speed on the UAV railway noise barrier dataset with a mean average precision (mAP) of 92.2 and a processing speed of 78.7 FPS.

Mamalis et al. 2023 [27] propose to reduce the global threat of the verticillium fungus on olive fields; this article emphasizes precise and early detection. The study uses the YOLO version 5 models to identify the verticillium fungi in olive trees using RGB data from unmanned aerial vehicles. The main goal is to compare model architectures and evaluate their performance. Model efficacy is measured by precision, recall, and mAP at different thresholds. YOLOv5 can detect olive trees and predict their health having pros and cons. This research improves olive cultivation disease control by using enhanced object detection to prevent verticillium fungal spread.

Mukto et al. 2024 [28] emphasize the social need for computerized crime detection technologies and their psychological effects on crime prevention. The suggested system uses efficient image processing and deep learning methods to detect and identify crime episodes. A combination of local binary pattern histogram, YOLOv5, and MobileNet performed best in rigorous testing. The system uses face, assault, and weapons detection to detect crimes in live camera feeds, adapting to weapon presence or absence. The real-time security system may struggle to detect crime in low-light or low-quality images, with concealed weapons, or with multiple processes, which could degrade performance on lower-spec hardware. Recognizing these limits, the system is a major step towards preemptive crime prevention, but it needs optimization and modification in different operational scenarios.

A multi-stage pipeline for power line segmentation, picture patch cutting, and patch classification for real-time breaking strand identification in UAV-based power line inspection is presented by Yan et al. 2023 [29]. To address power line thinness and strand breaking sample scarcity, our method uses normal power line images and rich local feature information. UAV edge computing resources can process lightweight segment and patch classification networks in real time. It is more accurate than previous object detection technologies and is compatible with incorporated edge computing devices, according to experiments. BA-NetV2, a power line segmentation network, adapts effectively to additional power line features, while multi-task learning gives the patch classification network exceptional accuracy. Strand breakage is a potential UAV-based power line fault detection technique that improves accuracy and real-time processing.

Ma et al. [30] offer a vision-based complete localization outline for UAVs using deep learning technologies like YOLO and DeepSORT to sense and trail broadcast keeps as milestones. Rflysim simulations test the framework's efficacy as a UAV navigates a landmark system with four transmission tower kinds. Comparing YOLOv5 versions and monitoring algorithms shows that YOLOv5-s coupled with DeepSORT is reliable for UAV location when landmark IDs are correct. The technology has a 10 m localization inaccuracy when compared to RTKGPS with a 1 km path. Unlike satellite imagery as a reference map, the suggested visual localization technique is memory-efficient and economically viable, allowing from beginning ending deployments on small UAVs. It presents a possible solution to UAV navigation and localization problems.

2.2 Problem description

Implementing a real-time monitoring and early warning system for pipeline surveillance presents multifaceted challenges. First and foremost, pipelines often cross remote or rugged terrain, making standard monitoring systems unsuitable. Real-time leak, corrosion, and damage detection is crucial to reducing accidents and environmental harm. However, rigorous protocols are needed to distinguish between serious risks and alarms that are unfounded to detect threats accurately and quickly, assuring continued operations. The use of UAVs and deep learning to solve these problems is appealing. UAVs (Unmanned aerial vehicles) can cross challenging terrain and provide full pipeline visual inspections from many points, increasing accessibility. Their speedy deployment allows them to quickly evaluate potential issues and implement solutions. UAVs with cameras and sensors may collect massive amounts of data, including photos and videos, for deep learning systems to analyze. Real-time data processing allows these systems to detect leaks and damage. This allows early detection and intervention. Despite their benefits, UAVs and deep learning face many challenges. Extracting useful features from data like photos or videos is tough and requires complex algorithms to recognize and measure pertinent data. Optimization is needed to choose the best for recognizing anomalies or categorization features. This ensures the monitoring system works at its best. Compatibility and data management challenges arise when integrating UAV data with monitoring systems and databases. Deep learning models need continual retraining and adaptation to generalize to new circumstances. This ensures strong performance in real-world conditions. Addressing these issues is essential for real-time pipeline surveillance and early alerting system uptake and reliability.

1. Develop UAV-based pipeline infrastructure assessment methods for thorough and efficient surveillance.
2. Develop deep learning methods to identify and classify pipeline data anomalies, then implement them.
3. Sophisticated methods for extracting features can help you find important information in collected data.

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4. To ensure the system is resilient and adaptable, it must be tested for detection accuracy, FAR (False Alarm Rate), response time, and system dependability in various operating conditions.

3. Proposed methodology

Figure 1 shows that the pipeline surveillance and early alerting system uses many components and procedures to identify and manage pipeline threats. The system focuses on pipes to identify dangers and irregularities during installation. Pipelines transport gasses and fluids over long distances. Pipelines are essential to this infrastructure. Pipeline operators can prevent accidents and leaks by maintaining them. This is done through monitoring. UAVs (Unmanned Aerial Vehicles), or drones, are used to collect pipeline system photographs. UAVs (Unmanned Aerial Vehicles) can explore pipeline networks, including inaccessible or remote regions, by gathering visual data in a variety of ways at low cost.

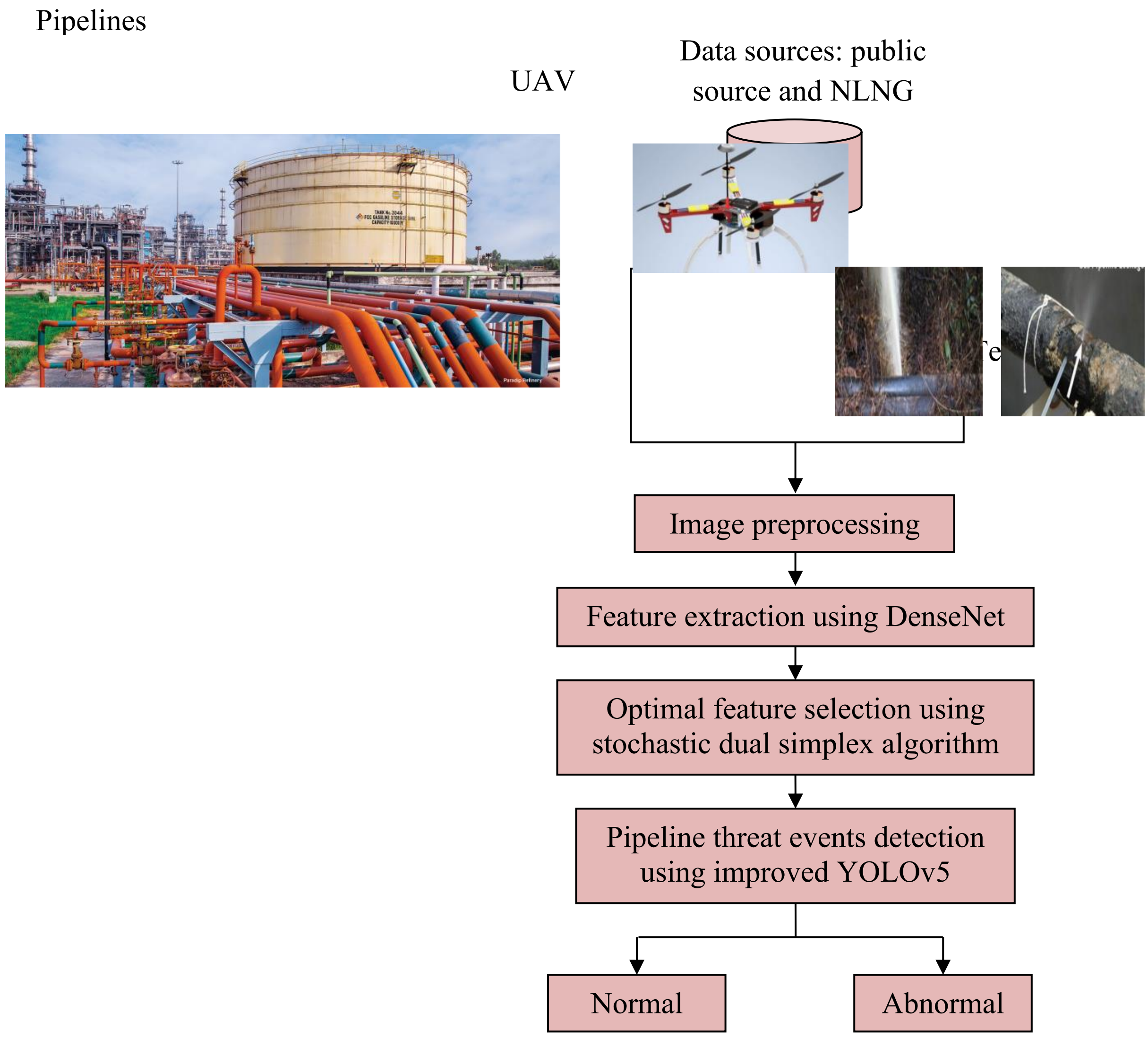

Fig. 1 Proposed pipeline monitoring and early warning system using improved YOLOv5

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Datasets are great for pipeline tracking systems training and testing. Test images from the collection are used to evaluate the monitoring system. These graphics illustrate a variety of real-world scenarios and settings to assure the system's durability and dependability. Before feature extraction, input photos undergo processing to remove noise and artifacts. Preprocessing steps including noise reduction, picture improvement, and normalization ensure analytical uniformity and accuracy. Preprocessed images are used to extract important features using DenseNet, a CNN architecture noted for its feature extraction. DenseNet extracts hierarchical features at several abstraction levels to capture pipeline picture local and global patterns. The randomized dual elemental technique refines the retrieved attributes through optimal feature selection. It finds the most valuable and discriminative traits while reducing redundancy. This guarantees that analysis uses only relevant data. The updated features are then fed into a deep recurring neural network-enhanced YOLOv5 object recognition model. Unknown objects are detected using this model. This hybrid model classifies pipeline photos as normal or unusual by identifying leaks, corrosion, and unlawful access. It detects potential threats.

3.1 Feature extraction using DenseNet

In the fields of computer vision and artificial intelligence, feature extraction takes critical information from raw data to represent input attributes. Feature extraction in pipeline monitoring involves identifying patterns or traits in pipeline photos. This method distinguishes leaks, cracks, and corrosion from normal conditions. DenseNet, commonly known as the densely convolutional network, is a framework for deep learning designed for image classification. Densely coupled convolutional layers form the structure. Each layer gets input from the layers before it, making feature reuse easier and network feature propagation more likely. This dense connection architecture lets the network learn highly distinctive characteristics at multiple abstraction levels for effective feature extraction. DenseNet feature extraction typically involves the following steps.

1. The pipeline image is input to DenseNet. Pixels in an image form a feature map. DenseNet processes input images using several convolutional layers.
2. Each convolutional layer extracts low-level visual characteristics. Characteristics include borders, surfaces, and shapes. DenseNet's dense layer connections enable feature reuse. Thus, features learned at lower layers can be reused and linked with characteristics learned at higher layers, creating more complete and prejudiced representations.
3. Feature mappings are created at each convolutional layer when the input image is transported. These feature maps, which are growing more abstract and sophisticated, capture input visual patterns.
4. A global mean pooling layer is often added after the convolutional layers converge to summarize the recovered properties across all dimensions of space. This produces a feature vector, a simplified version of the input image.
5. The DenseNet model produces a feature vector with a high-level model of the pipelined image. These features contain crucial pipeline characteristics and structural information that can be used for later study, such as anomaly identification or pipeline categorization.

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By using the DenseNet architecture for feature extraction, the pipeline monitoring system can effectively capture rich and informative representations of pipeline images, enabling accurate detection of abnormalities and potential threats.

3.2 Optimal feature selection using stochastic dual elemental algorithm

In machine learning and data evaluation, feature choice includes choosing the most important and useful features from a dataset and removing the rest. It improves model performance, computing complexity, and interpretability by focusing on discriminative properties. A dual elemental method solves linear programming issues. This is the probabilistic dual elemental algorithm. In feature selection, the random dual elemental technique is modified to search for a solution space and find the optimal collection of features to maximize predictive model performance. This is done through feature selection. Sequential dual elemental algorithm feature selection often involves the following phases:

1. Randomly or heuristically select an initial subset of features.
2. The subset features are used to train a model for prediction.
3. The probabilistic dual elemental technique iteratively explores alternate feature subsets, adding or removing features to improve model performance. The program considers potential properties and evaluates their impact on the model's efficiency during each iteration.
4. It uses twin elemental techniques to find the optimum feature subset efficiently. It involves iteratively adjusting the dual variables to improve the target function while maintaining feasibility.
5. When a set of convergence criteria is met, such as a preset number of iterations or a threshold model efficiency enhancement, the procedure ends.
6. After optimization, the final set of characteristics is chosen. These features are most relevant and instructive for the predicting task being done.

In a space with n dimensions, a straight line is a geometric entity made up of (s + 1) points $(p_0,\dots p_b)$. In two-dimensional space, a triangle, for instance, is a elemental. The elemental method relies on comparing the values of the (s + 1)th position with those of other elemental points in order to iteratively approach the optimal point. Here is how to create the g-th vertices of an ordinary polygon of size b in b-dimensional space.

$$P_g = p_0 + xU_g + \sum_{\substack{t=1 \\ s\neq g}}^{b} yU_t \tag{1}$$

Where p_0 then U_t are the early improper fact and component trajectory together with alliance t, individually. x and y are expressed as follows.

$$x = \frac{m}{b\sqrt{2}}\left(\sqrt{b+1}+b-1\right) \tag{2}$$

$$y = \frac{m}{b\sqrt{2}}\left(\sqrt{b+1}-1\right) \tag{3}$$

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For attainment the ideal resolution, working tackles are utilized, deforming elemental scheme geometrically. This process tips to switch the present nastiest apex by a improved fact which is originate by elemental procedures. The distorted apexes, called reproduced opinion (p_R), prolonged opinion (p_E), and slender opinion (p_D), are formulated by

$$p_R = (1+\alpha)\overline{p_0} - \alpha\, p_i,\ \ \alpha > 0 \tag{4}$$

$$p_E = \gamma P_R + (1+\gamma)\overline{p_0} \qquad \gamma > 0 \tag{5}$$

$$p_D = \beta P_i + (1+\beta)\overline{p_0} \qquad 0 \le \beta \le 1 \tag{6}$$

where α, γ , and β are the reflection, expansion, and contraction coefficients, respectively. During these transformations, the centroid of all vertices (p_g) excluding the worst point (p_i) is $\overline{p_0}$. Early twin elementals are dispersed arbitrarily in the hunt interplanetary seeing the chance cohort of both apexes with unchanging delivery. The early twin elemental hires the elemental operatives, and its scope a seeing the supreme break (m_{Max}) is specified by

$$m = Rand(0,\ m_{Max}) \tag{7}$$

Through the h-th restatement, the nastiest apexes of elementals in the hunt interplanetary are substituted by usual supply instructions which are demonstrated as follows.

$$\overset{*\,(h)}{p_{i_t}} = p_{i_t}^{(h)} + F^{(h)}\overline{p}_0^{(h)} \tag{8}$$

where $\overset{*\,(h)}{p_{i_t}}$ is the novel reproduced opinion calculated by the nastiest opinion of each elemental ($p_{i_t}^{(h)}$), and $F^{(h)}$ is the usual delivery of the tested answer in the h-th repetition and the t-th elemental. The centroid of all elementals and the probability density function of the normal distributed elementals are then expressed as follows.

$$\overline{p}_0^{(h)} = \sum_{t=1}^{b_t} \overline{p}_{0_t}^{(h)} \tag{9}$$

$$F(p_i \mid \Sigma) = \frac{1}{\sqrt{2\pi \mid \Sigma \mid}} \cdot Exp\left(- \frac{(p_i - \overline{p}_0)^S\, \Sigma^{-1}(p_i - \overline{p}_0}{2} \right) \tag{10}$$

where b_t is the number of elementals in search space. The covariance matrix of elementals (Σ) is formulated as follows.

$$\Sigma_{KL} = e\left[(p_{i_K} - \overline{p}_{0_K})\,(p_{i_L} - \overline{p}_{0_L})^S\right] \tag{11}$$

where Σ is the predictable worth of the nastiest fact in each elemental. K and L are the directories of all elemental in the field of K, L = 1,..., b_t . Then, the worldwide finest fact can

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be gotten by averaging the cost of every elemental in hunt interplanetary. The strictures of the dual elemental operatives are arbitrarily altered as follows.

$$\alpha = \alpha_{Max} Rand(0,1) \tag{12}$$

$$\gamma = 1 + (\gamma_{Max} - 1) Rand(0,1) \tag{13}$$

$$\beta = \beta_{Max} Rand(0,1) \tag{14}$$

where α_{Max}, γ_{Max}, and β_{Max} are the SDSA parameters. Noted that the proposed algorithm is terminated when the number of iterations exceeds a maximum iteration (h_{Max}).

3.3 Pipeline threat events detection using improved YOLOv5

The integration of YOLOv5 with a deep recurrent neural network (RNN) for pipeline threat events detection, referred to as "improved YOLOv5," represents a significant advancement in real-time monitoring and early warning systems for pipeline infrastructure. YOLOv5 is a state-of-the-art object detection model known for its speed and accuracy in detecting objects in images or videos. By merging YOLOv5 with a deep RNN, the algorithm can detect threats and evaluate image temporal sequences to anticipate future occurrences. The main object detection framework is YOLOv5. Divide the input image into a grid of cells and estimate box boundaries and class probabilities for objects in each cell. Fast and accurate, YOLOv5 is ideal for real-time pipeline monitoring. The system design includes YOLOv5 and a deep RNN. RNNs process input sequences and store memory to model sequential data. The RNN can identify temporal dependencies and patterns in image sequences, making it useful for time-series data analysis like video analysis. Real-time video streams are used to train the YOLOv5-RNN model to detect pipeline danger events like cracks, leaks, and other anomalies. YOLOv5 detects objects of interest in each video frame, while the RNN analyses the temporal sequence to find threats. The upgraded YOLOv5 pipeline risk identification system monitors pipeline infrastructure in real time using deep RNN. The system continuously scans UAV or other video streams to identify dangers. Anomalies can trigger early warning alarms, allowing operators to manage risks and prevent incidents. Deep RNNs capture increasingly complicated input-output interactions by feeding data from one layer of recurring units to the next. The number of filters used to mix the input with 1D convolutional layer data determines the activation function in this model. Functional graph dimension is derived as follows.

$$FA_{I2} = \frac{H_{I1} - Dk_I + 2X_t}{T_{th}} + 1 \tag{15}$$

where FA_{I2} denotes the height of the feature map, H_{I1} denotes the input height before convolution, Dk_I denotes the convolutional kernel height, X_t denotes the pad size, denotes the T step size, Dk_I denotes the convolutional kernel height. Local input features are extracted using a single convolutional kernel.

$$HI_{1M}(h) = F(ZA_M \cdot P(h : h + M - 1) + N) \tag{16}$$

$$HI_{1M} = [HI_{1M}(1); HI_{1M}(2) \ldots HI_{1M}(FA_{I2})] \tag{17}$$

$$HIr_{1M} = \mathrm{Re}\,lu(HI_{1M}) \tag{18}$$

where ZA_M denotes the convolution kernel function with height M and HI_1 denotes the output after transformation. Accordingly, the maximum pooling layer is used to collect all inference results about the extracted text feature set.

$$HIrx_{1M} = Max(HI_{1M}) \tag{19}$$

$$HI_1 = concatenate\left(HIrx_{1M_1}, HIrx_{1M_2}\right) \tag{20}$$

The integration of YOLOv5 with a deep RNN represents a powerful approach to pipeline threat detection, offering both speed and accuracy in real-time monitoring applications. This advanced system provides critical capabilities for ensuring the safety of pipeline infrastructure, helping to prevent accidents, leaks, and other hazardous events.

4. Results and discussion

In this section, we validate the performance of proposed and existing pipeline monitoring system using datasets which obtained from the publicly available source and the Nigerian Liquefied Natural Gas (NLNG) research department. The experimental environment was demonstrated on Ubuntu 18.04 functioning scheme, with an Intel(R) Xeon(R) Sliver 4110 CPU@2.10HZ CPU formation, a GeForce GTX 1080ti graphics card selected, 11GB of video memory, and PyTorch version 1.7.0 and the Python environment used to construct the runtime environment. Multiple indexes are used to comprehensively evaluate the prediction results, such as Accuracy, Precision, Recall, F-measure, and AUC Score. The results of proposed improved YOLOv5 system is compared with the existing benchmark systems such as linear regression (LR), random forest (RF), k-nearest neighbor (k-NN), support vector machine (SVM), XGboosting, YOLOv4, YOLOv5 and convolutional neural network (CNN) [31].

4.1 Dataset description

Both the NLNG (Nigerian Liquefied Natural Gas) study division and a publicly available source provided the datasets used in this investigation [32]. All told, there are around 204 pictures here, depicting oil pipelines, pipes with leaks, people wearing PPE, and people not wearing PPE. Education, confirmation, and test data were partitioned from the datasets in the following proportions: 7:2:1. With a batch size of 10, an input shape of 224×224×3, and 100 epochs of transfer learning on top of the TensorFlow framework, they were utilized to train a ResNet50 model with the help of the Google collaborator. Using the 18,000 photos as input, the trained CNN model produced 8196 parameters that could be further trained. Table 1 presents a detailed description of the dataset used in this study for pipeline monitoring and threat detection. The dataset has two main sets: training and testing. The training set comprises 11,000 samples, 6,000 of which are "Normal" and 5,000 "Abnormal." Different

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samples make up the training set. Pipeline threat detection machine learning models have been developed and optimized using representative data. The testing set has 7,000 samples, with 3,500 each for the "Normal" and "Abnormal" classes. This testing set evaluates trained models on new data and their predictive ability. The dataset contains 18,000 samples, 9,500 of which are "Normal" and 8,500 "Abnormal." This dataset allows accurate and reliable pipeline threat identification system training and evaluation by representing pipeline conditions thoroughly and balancedly. Figure 2 shows dataset test photos.

Table 1 Dataset description

Case	Number of samples		
	Normal	Abnormal	Total
Training	6000	5000	11000
Testing	3500	3500	7000
Total	9500	8500	18000

(a)

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Fig. 2 Test sample images from dataset (a) publicly available source (b) NLNG research department

4.2 Results comparison of various pipeline monitoring systems on publicly available source

Table 2 provides a comparative analysis of existing pipeline monitoring systems based on publicly available sources. The results in Fig. 3 present a comparative analysis of various pipeline monitoring systems based on publicly available sources, focusing on training samples. The maximum accuracy 96.235% is achieved by our proposed improved YOLOv5 system which is 52.828%, 46.225%, 39.621%, 33.018%, 26.414%, 19.811%, 13.207% and 6.604% efficient than the existing LR, RF, k-NN, SVM, XGboosting, CNN, YOLOv4 and YOLOv5 systems. For precision, our proposed Improved YOLOv5 system achieves a maximum precision of 94.568% during the training process. Compared to existing systems, it demonstrates efficiency gains of 52.828%, 46.225%, 39.621%, 33.018%, 26.414%, 19.811%, 13.207%, and 6.604% over LR, RF, k-NN, SVM, XGboosting, CNN, YOLOv4, and YOLOv5, respectively. Regarding recall, Improved YOLOv5 attains peak value of 94.012%, shows its effectiveness in capturing pipeline threats. This performance represents efficiency improvements of 52.828%, 46.225%, 39.621%, 33.018%, 26.414%, 19.811%, 13.207%, and 6.604% over LR, RF, k-NN, SVM, XGboosting, CNN, YOLOv4, and YOLOv5 systems, respectively. In terms of F-measure, our proposed system achieves a maximum score of 94.289%, indicating its ability to balance precision and recall effectively. Compared to existing systems, it exhibits efficiency gains of 52.828%, 46.225%, 39.621%, 33.018%, 26.414%, 19.811%, 13.207%, and 6.604% over LR, RF, k-NN, SVM, XGboosting, CNN, YOLOv4, and YOLOv5, respectively. Lastly, considering the AUC, Improved YOLOv5 achieves top performance of 94.895%. It represents efficiency improvements of 52.828%, 46.225%, 39.621%, 33.018%, 26.414%, 19.811%, 13.207%, and 6.604% over LR, RF, k-NN, SVM, XGboosting, CNN, YOLOv4, and YOLOv5 systems, respectively.

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International Journal of Applied Mathematics
Volume 38 No. 5s, 2025
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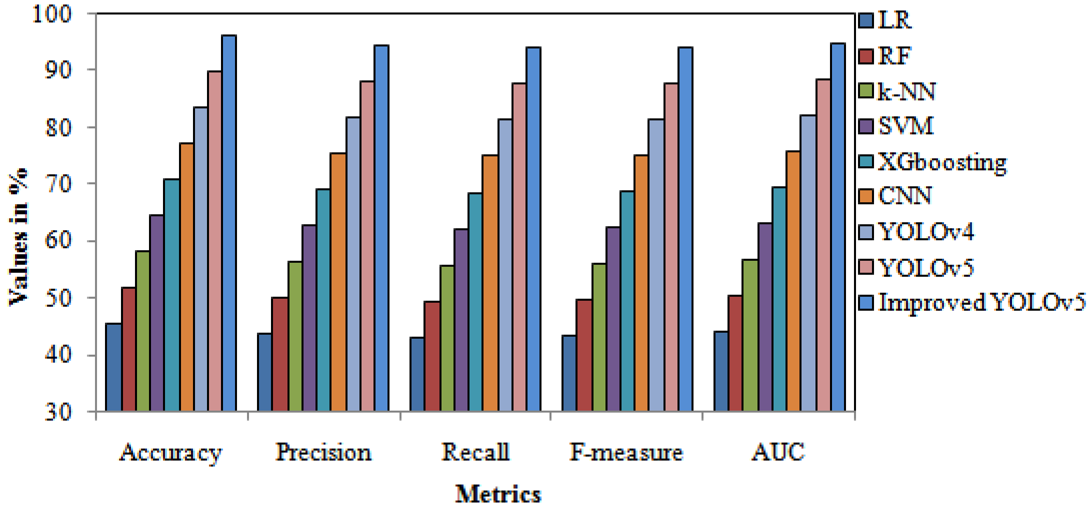

Fig. 3 Results comparison for publicly available source with training samples

Table 2 Comparative analysis of pipeline monitoring systems on publicly available source

Pipeline monitoring system	Values in %				
	Accuracy	Precision	Recall	F-measure	AUC
	Training				
LR	45.396	43.729	43.173	43.449	44.056
RF	51.751	50.084	49.528	49.804	50.411
k-NN	58.106	56.439	55.883	56.159	56.766
SVM	64.461	62.794	62.238	62.514	63.121
XGboosting	70.815	69.148	68.592	68.869	69.475
CNN	77.170	75.503	74.947	75.224	75.830
YOLOv4	83.525	81.858	81.302	81.579	82.185
YOLOv5	89.880	88.213	87.657	87.934	88.540
Improved YOLOv5	96.235	94.568	94.012	94.289	94.895
	Testing				
LR	35.038	33.705	32.204	32.937	32.860
RF	42.890	41.557	40.056	40.793	40.712
k-NN	50.742	49.409	47.908	48.647	48.565
SVM	58.595	57.262	55.761	56.501	56.417
XGboosting	66.447	65.114	63.613	64.355	64.269

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Volume 38 No. 5s, 2025
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CNN	74.299	72.966	71.465	72.208	72.122
YOLOv4	82.151	80.818	79.317	80.061	79.974
YOLOv5	90.004	88.671	87.170	87.914	87.826
Improved YOLOv5	97.856	96.523	95.022	95.767	95.679

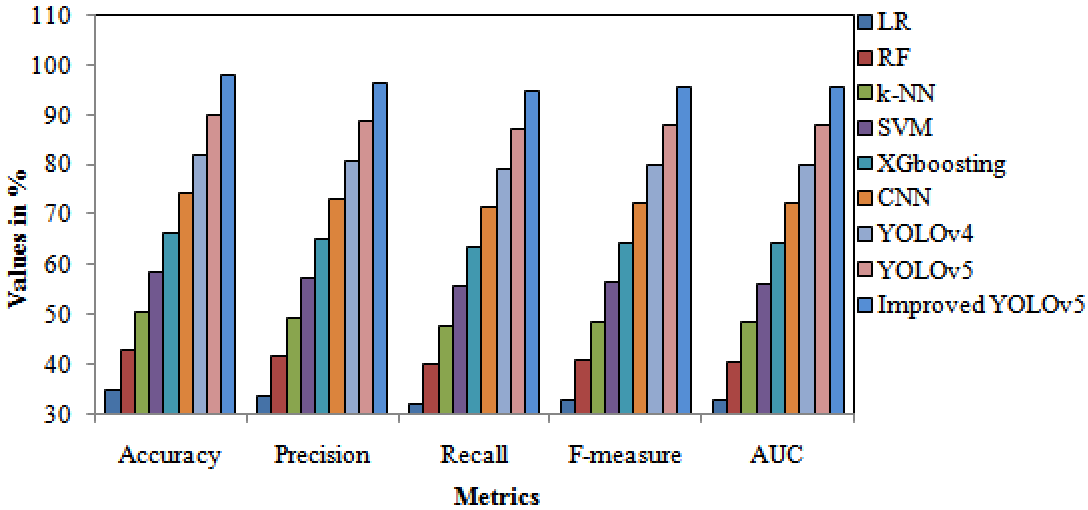

Fig. 4 Results comparison for publicly available source with testing samples

For the testing samples, our Improved YOLOv5 system achieves exceptional performance as shown in Fig. 4, with a maximum accuracy of 97.856%. Compared to existing systems, it demonstrates efficiency gains of 62.818%, 55.966%, 46.114%, 39.261%, 31.409%, 23.557%, 15.705%, and 7.853% over LR, RF, k-NN, SVM, XGboosting, CNN, YOLOv4, and YOLOv5 systems, respectively. In terms of precision, Improved YOLOv5 attains a peak value of 96.523%. This represents efficiency improvements of 62.818%, 55.966%, 46.114%, 39.261%, 31.409%, 23.557%, 15.705%, and 7.853% over LR, RF, k-NN, SVM, XGboosting, CNN, YOLOv4, and YOLOv5 systems, respectively. Regarding recall, our proposed system achieves a maximum score of 95.022%, showcasing its effectiveness in capturing pipeline threats during testing. This performance represents efficiency gains of 62.818%, 55.966%, 46.114%, 39.261%, 31.409%, 23.557%, 15.705%, and 7.853% over LR, RF, k-NN, SVM, XGboosting, CNN, YOLOv4, and YOLOv5 systems, respectively. In terms of F-measure, Improved YOLOv5 achieves a top performance of 95.767%. It represents efficiency improvements of 62.818%, 55.966%, 46.114%, 39.261%, 31.409%, 23.557%, 15.705%, and 7.853% over LR, RF, k-NN, SVM, XGboosting, CNN, YOLOv4, and YOLOv5 systems, respectively. Lastly, considering the AUC, Improved YOLOv5 achieves a maximum value of 95.679%. This represents efficiency improvements of 62.818%, 55.966%, 46.114%, 39.261%, 31.409%, 23.557%, 15.705%, and 7.853% over LR, RF, k-NN, SVM, XGboosting, CNN, YOLOv4, and YOLOv5 systems, respectively.

4.3 Results comparison of pipeline monitoring systems on NLNG research department

Table 3 provides a comparative analysis of existing pipeline monitoring systems based on NLNG research department dataset. When evaluating the training samples from the NLNG

International Journal of Applied Mathematics
Volume 38 No. 5s, 2025
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research department dataset, our proposed Improved YOLOv5 system shows remarkable performance shown in Fig. 5, achieving an accuracy of 95.525%. Comparing to existing systems, it demonstrates efficiency gains of 52.784%, 46.187%, 39.589%, 32.991%, 26.393%, 19.795%, 13.197%, and 5.599% over LR, RF, k-NN, SVM, XGboosting, CNN, YOLOv4, and YOLOv5 systems, respectively. In terms of precision, Improved YOLOv5 achieves a top performance of 94.710%. This represents efficiency improvements of 52.784%, 46.187%, 39.589%, 32.991%, 26.393%, 19.795%, 13.197%, and 5.599% over LR, RF, k-NN, SVM, XGboosting, CNN, YOLOv4, and YOLOv5 systems, respectively. Regarding recall, our proposed system attains a maximum score of 94.568%, showcasing its effectiveness in capturing pipeline threats during training. It represents efficiency gains of 52.784%, 46.187%, 39.589%, 32.991%, 26.393%, 19.795%, 13.197%, and 5.599% over LR, RF, k-NN, SVM, XGboosting, CNN, YOLOv4, and YOLOv5 systems, respectively. In terms of F-measure, Improved YOLOv5 achieves a top performance of 94.639%. It represents efficiency improvements of 52.784%, 46.187%, 39.589%, 32.991%, 26.393%, 19.795%, 13.197%, and 5.599% over LR, RF, k-NN, SVM, XGboosting, CNN, YOLOv4, and YOLOv5 systems, respectively. Lastly, considering the AUC, Improved YOLOv5 achieves maximum value of 95.321%. It represents efficiency improvements of 52.784%, 46.187%, 39.589%, 32.991%, 26.393%, 19.795%, 13.197%, and 5.599% over LR, RF, k-NN, SVM, XGboosting, CNN, YOLOv4, and YOLOv5 systems, respectively.

Table 3Comparative analysis of pipeline monitoring systems on NLNG research department dataset

Pipeline monitoring system	Values in %				
	Accuracy	Precision	Recall	F-measure	AUC
	Training				
LR	42.741	41.926	41.784	41.855	42.537
RF	49.339	48.524	48.382	48.453	49.135
k-NN	55.937	55.122	54.980	55.051	55.733
SVM	62.535	61.720	61.578	61.649	62.331
XGboosting	69.133	68.318	68.176	68.247	68.929
CNN	75.731	74.916	74.774	74.845	75.527
YOLOv4	82.329	81.514	81.372	81.443	82.125
YOLOv5	88.927	88.112	87.970	88.041	88.723
Improved YOLOv5	95.525	94.710	94.568	94.639	95.321
	Testing				
LR	36.038	35.442	34.392	34.909	35.266
RF	43.673	43.077	42.027	42.546	42.901

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k-NN	51.309	50.713	49.663	50.183	50.537
SVM	58.945	58.349	57.299	57.819	58.173
XGboosting	66.581	65.985	64.935	65.456	65.809
CNN	74.217	73.621	72.571	73.092	73.445
YOLOv4	81.852	81.256	80.206	80.728	81.080
YOLOv5	89.488	88.892	87.842	88.364	88.716
Improved YOLOv5	97.124	96.528	95.478	96.000	96.352

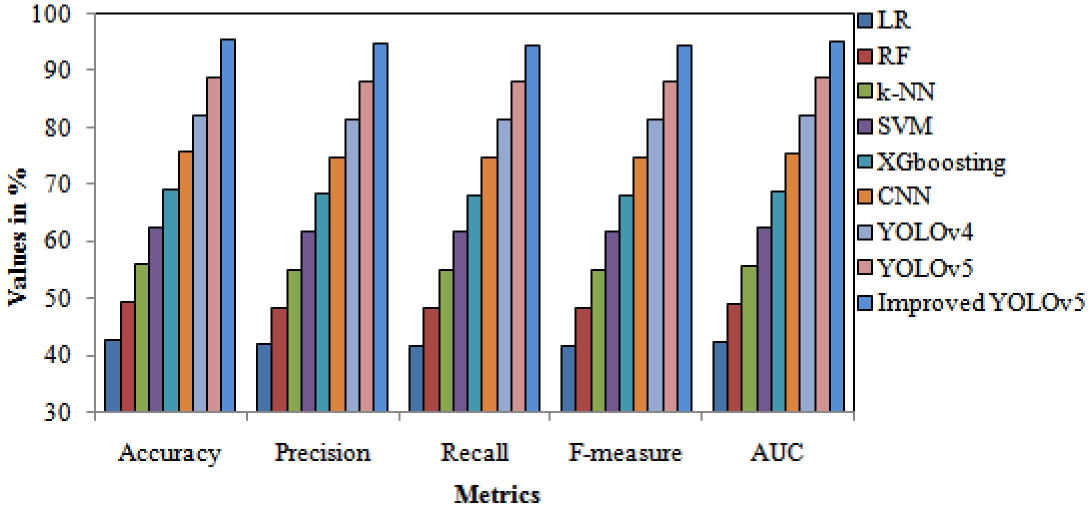

Fig. 5 Results comparison for NLNG research department dataset with training samples

When analyzing the testing samples from the NLNG research department dataset, our Improved YOLOv5 system shows exceptional performance shown in Fig. 6, achieving an accuracy of 97.124%. Comparing to existing systems, it showcases efficiency gains of 52.586%, 45.851%, 39.215%, 32.579%, 25.943%, 19.307%, 12.671%, and 5.836% over LR, RF, k-NN, SVM, XGboosting, CNN, YOLOv4, and YOLOv5 systems, respectively. In terms of precision, Improved YOLOv5 achieves top performance of 96.528%. It represents efficiency improvements of 52.586%, 45.851%, 39.215%, 32.579%, 25.943%, 19.307%, 12.671%, and 5.836% over LR, RF, k-NN, SVM, XGboosting, CNN, YOLOv4, and YOLOv5 systems, respectively. Regarding recall, our proposed system attains a maximum score of 95.478%, indicating its effectiveness in capturing pipeline threats during testing. It represents efficiency gains of 52.586%, 45.851%, 39.215%, 32.579%, 25.943%, 19.307%, 12.671%, and 5.836% over LR, RF, k-NN, SVM, XGboosting, CNN, YOLOv4, and YOLOv5 systems, respectively. In terms of F-measure, Improved YOLOv5 achieves top performance of 96.000%, shown its efficiency in balancing precision and recall. This represents efficiency improvements of 52.586%, 45.851%, 39.215%, 32.579%, 25.943%, 19.307%, 12.671%, and 5.836% over LR, RF, k-NN, SVM, XGboosting, CNN, YOLOv4, and YOLOv5 systems, respectively. Lastly, considering the AUC, Improved YOLOv5 achieves a maximum value of 96.352%. It represents efficiency improvements of 52.586%,

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45.851%, 39.215%, 32.579%, 25.943%, 19.307%, 12.671%, and 5.836% over LR, RF, k-NN, SVM, XGboosting, CNN, YOLOv4, and YOLOv5 systems, respectively.

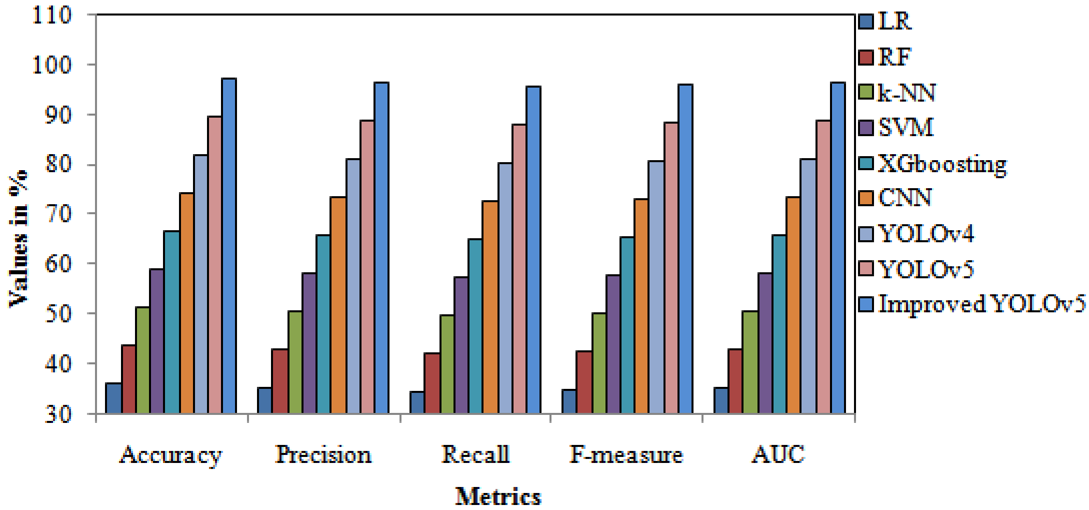

Fig. 6 Results comparison for NLNG research department dataset with testing samples

5. Conclusion

We have proposed the real-time monitoring and early warning system for UAV integrated with pipeline monitoring using deep learning with YOLOv5. The hybrid DenseNet with stochastic dual elemental algorithm for feature extraction and optimization which extracts more deep features from the gathered pipeline images and optimizes the feature to selects best of them. We then integrate YOLOv5 with deep recurrent neural network (improved YOLOv5) for pipeline threat events detection which ensures the real-time monitoring and early warning like cracks and leakages. To validate the performance of proposed and existing systems using the publicly available sources and the results show their effectiveness. The maximum testing accuracy is achieved by an improved YOLOv5 is 97.856% and 97.124% for both datasets, respectively which 12.92% and 14.456% higher than the existing state-of-art systems. Our Improved YOLOv5 system consistently outperforms existing pipeline monitoring systems across various datasets and testing scenarios. When comparing the accuracy, precision, recall, F-measure, and AUC metrics, Improved YOLOv5 consistently demonstrates superior performance, achieving significant efficiency ranging from 5.836% to 2.586% over existing systems. The integration of deep recurrent neural networks with YOLOv5 in our Improved YOLOv5 system contributes to its exceptional performance, enabling effective capture of spatial and temporal variations in pipeline conditions.

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