IOT-HML: A hybrid machine learning technique for IoT enabled industrial monitoring and control system

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Summary
Industrial 4.0 makes manufacturers more vulnerable to current challenges and makes it easier to adapt to market changes. It is essential to focus on monitoring and controlling the production system before complex accidents occur. To overcome above research gaps, we shift to industrial 4.0, which combine IoT and mechanism learning for industrial monitor and manage. Here, we propose a hybrid machine learning technique for IoT enabled industrial monitoring and control system (IoT-HML). The main goal of the research is to overcome the issues of information security and control systems by developing a hybrid machine learning technique for IoT enabled industrial monitoring and control system (IoT-HML). Compared to the existing AODV protocol, the proposed C-IWO based routing protocol outperformed efficiently in terms of 19.2% average delay, 12.7% average energy consumption, 10.26% average throughput, 3.8% average delivery ratio, and 16.33% average loss ratio, respectively. In addition, the accuracy 98.5%, sensitivity 97.3%, specificity 98.2%, precision 98.35%, recall 98.32%, and F-measure 97.49% of proposed CP-LNN technique is very high compare to obtainable state-of-art classifiers.

KEYWORDS
cluster head (CH), clustering, hybrid machine learning, industrial 4.0, IoT enabled industrial

1 | INTRODUCTION

In the future, with the advent of Industry 4.0, computers will be able to interact and make decisions without human intervention. The combination of web physics system, the Internet of Systems (IoS) and Internet of Things (IoT) allows Business 4.0 to become a better industry. The manufacturing industry is busy converting goods, materials or products into new products. Plants, mills, or factories that produce products for general consumption are often owned by manufacturers. Machinery and tools are often used in the manufacturing process. This includes food, chemicals, textiles, machinery, and equipment.1 It contains all the refined metals and minerals extracted from the ores. This includes wood, timber, and wood products. Production is the production of materials using labor, machinery, equipment, chemical or biological processing or work. This is the essence of the second sector of the economy. The term can cover a wide range of person behavior, from handicraft to high-tech, but it is also often used for manufacturing mean, in which raw materials are converted into large-scale finished goods. Such products are available to other manufacturers of other complex products.2 The IoT model, first introduced by Kevin Ashton in 1998, has paying attention a lot of notice in education and manufacturing. By incorporating mobile adapters into short gadgets and everyday distances, IoT allows a new dimension of communication between people and objects, giving a whole original measurement to the world of in sequence and communiqué.3

There is no doubt that this has a huge impact on many aspects of daily life and the behavior of potential users. From a private consumer perspective, the most obvious outcome of IoT is employment and the domestic sector.4 In this regard, appropriate living conditions, smart homes, offices, hygiene and modern training are just a few examples of the situation in which a new model will play an important role in the future. Similarly, from the point of view of business customers, very clear results can be equated with areas such as automation, industrial construction, logistics, business process management, and intelligent transportation of people and goods.5 Many scientific endeavors in the manufacturing sector reflect such an
impact on IoT technologies. The Organizations information in a process environment related to the assembly of IoT large aircraft components. Process automation uses a general application model and IoT framework to simplify the process environment. The increasing impact of IoT on enterprise systems (ES) for modern manufacturing domains was discussed. The relationship between IT infrastructure and enterprise organizations was examined to identify technical gaps in companies’ adoption of IoT policies as IT infrastructure. The analyzed IoT technology applications are considered within the framework of cloud computing (CC); CC & IoT based cloud manufacturing (CMFG) service system (also known as CCIODCMFG) and its structure. Based on IoT, an intelligent concept of production sources and available architecture was developed and proposed. Its key technologies are described in the context of cloud-based building systems; a prototype has been developed to change attitudes. The evolution of the industrial ecosystem is related to the advancement of information technology (IT) systems.

Product communication, processing, usage logic and decision making are the factors that support the development of production methods. In addition, companies rely heavily on a variety of professional IT tools and solutions to manage different positions in their industry. Today, the rapid growth of miniature systems and the general interest in global inventions are leading to the next generation of industrial habitats that can use low power networks to monitor and control operations. Most of these systems work with modern microelectronics and wireless data communications. Some technologies such as wireless sensor and actuator networks (WSANs) are increasingly used in industrial processes to monitor and control industrial processes and to detect short circuits containing energy at short distances. The most effective use of an IoT-enabled product is direct data reporting. It allows users to make accurate decisions based on such data. Big Data Analytics is the process of evaluating various databases, methods, contacts, market trends, and other useful information that allow companies to make informed decisions. This includes the processing of any information that is considered to refer to an item or person, such as a user ID or age. The largest data analysis will be used in the operation of the most important construction plants.

Our contributions:

• A hybrid machine learning technique is proposed for IoT enabled industrial monitoring and control system (IoT-HML) to overcome problems in both information security issues with accurate monitoring and control system.

• The cat induced wheel optimization (IWO) algorithm was used for clustering which consists of cluster formation and CH selection process.

• The cuckoo search algorithm was utilized for the optimal best path computation among multiple paths.

• A coach and player learned neural network (CP-LNN) is used for monitoring the industry and preventing accidents by basic control strategies.

The rest of this research is as follows. Section 2 discusses the recent literature works. Section 3 states the problem, and Section 4 demonstrates the proposed work. Section 5 illustrates the results and discussion of the research work. Finally, Section 6 summarizes the research.

2 | RELATED WORKS

Christou et al.21 presented the architecture, design, practical implementation, and evaluation of an end-to-end platform that addresses the challenges. Selim et al.22 explored an analytical study of detecting anomalies, malicious activities, and cyber-attacks in a cyber-physical of critical water infrastructure in the IoT infrastructure.

Selim et al.23 developed a Machine Learning Model for Malicious Activities Recognition in Water-based Industrial Internet of Things (MAR-WIoT). Vakili et al.24 developed different machine learning algorithms to the dataset and it was found that AdaBoost has better accuracy and performance compared to other algorithms and when it comes to deep learning CNN had the best accuracy compared to other ones.

A secure demand-side management (DSM) engine was proposed using machine learning (ML) for the Internet of Things (IoT)-enabled grid.25 An open-source technology based smart system to predict the irrigation requirements of a field using the sensing of ground parameter like soil moisture, soil temperature, and environmental conditions along with the weather forecast data from the Internet.26 Patel et al.27 developed a scaled-down prototype of an IoT-enabled datalogger for photovoltaic system that is installed in a remote location where human intervention was not possible due to harsh weather conditions or other circumstances. Ahmed et al.28 aimed to examine the convergence of blockchain technology and artificial intelligence, a unique driver towards technological transformation in intelligent and sustainable IoT applications.

3 | PROBLEM METHODOLOGY AND SYSTEM MODEL

3.1 | Problem methodology

The robust overall structure of the IoT Industrial Control System is determined by a reliable operating module that measures reliability and controls for optimal performance. Wang29 Sensitive environment is very difficult for IoT. The cluster-based routing system used to ensure the reliability
and security of a data source maintains the routing protocol efficiently and reliably. Parallel node display is recommended for scenes with multiple malicious nodes. Abnormal attacks disturb the Bayesian dynamic balance between the striker and the detection node. Industry 4.0 further weakens manufacturers of current challenges and makes it easier to adapt to changes in the market. This will accelerate innovation and make it more customer-oriented, leading to faster design processes. It is important to focus on monitoring and controlling the production system before complex accidents occur.

Industrial IoT is defined as a network of devices, machinery and sensors connected to each other and to the Internet, with the purpose of collecting data and analyze it to apply this information in continuous process improvement. In this industrial IoT applications, it provides access to real-time supply chain information by tracking materials in transit, products, and equipment as they move through the supply chain. Through effective reporting manufacturers are able to collect and feed the delivery information into systems like ERP, PLM, and so forth. Industrial IoT does not replace, but works together with automation, human-machine interface (HMI), MES, ERP, enterprise manufacturing intelligence (EMI), and analytics, adding benefits. The fourth industrial revolution has been underway for a while now. People call it digital transformation, Industry 4.0, digitalization, or just smart manufacturing. Regardless of the name, all the new technology coming from this revolution is driving real economic benefits and helping fuel a big boom in manufacturing around the world. Most manufacturing companies are already undertaking some kind of Industry 4.0 project or are planning to in the very near future. The Industrial Internet of Things (IIoT), artificial intelligence (AI), augmented/virtual reality (AR/VR), digital twins, digital threads, cloud and edge computing, and a whole lot more are all part of Industry 4.0, but maybe none more so than the IIoT.

When an existing intelligence system fails to respond to a pre-disaster situation, its rapid operation can cause the server’s IoT components to crash for years. Moreover, an industrial control system facing information security problems in recent times because of the nature of IoT, which affects the evaluation of abnormal predication. To overcome above research gaps, we shift to industrial 4.0, which combine IoT and mechanism learning for industrial monitor and organize. We propose a hybrid machine learning technique for IoT enabled industrial monitoring and control system (IoT-HML). The main goal of the research is to overcome the issues of information security and control systems by developing a hybrid machine learning technique. Here, we concentrate both information security issues with accurate monitoring and control system. The major donations of planned IoT-HML technique are summarizing as follows:

- The first section of planned IoT-HML scheme is to introduce the cat induced wheel optimization algorithm for cluster formation. The process consists of clustering and cluster head (CH) selection. The source node forward information to destination through CH only which avoids the unwanted data loss and improve the security, because the information travel through trusted path.
- For route selection process, we utilize the cuckoo search algorithm to compute the optimal best path among multiples.
- In second section, we illustrate a coach and player learned neural network (CP-LNN) for monitoring the industrial and prevent from accidents by basic control strategies.
- Finally, the proposed IoT-HML system can evaluate with different set of data's to prove the effectiveness.

3.2 System architecture of proposed IoT-HML system

Figure 1 shows the proposed system model. The system consists of an industrial environment. In order to detect the temperature, pressure and the speed three different sensors are used, that is, temperature sensor, pressure sensor and speed sensor. For monitoring the data transmission data monitoring center is used. The vehicles will take data from the base station and it is send it to nearby nodes. The terminal ranges are used to identify the nearest node location. The nodes are clustered. The paths are formed between the nodes for the transmission. From the multiple nodes aggregated nodes are identified. The access point, base station is there for proper data transmission. The data that are sending from the sensors are given to the cloud platform after that only it will be given to the monitoring unit. When the sensor wants to send the data to the vehicle it will check for the vehicle which is free by sending the request to the base station. The base station will check for the free vehicle. In case if the entire vehicle is busy then the sensor will hold the data in the sensor node until the base station send the acknowledgement related to the free vehicle. At that period of time the internal process of the industry will be in an interrupt form.

4 HYBRID MACHINE LEARNING TECHNIQUE FOR IOT ENABLED INDUSTRIAL MONITORING AND CONTROL SYSTEM (IOT-HML)

4.1 Clustering using cat induced wheel optimization (IWO)

The purpose of clustering is to divide the whole network into separate parts to ensure the reliability and the security data. Then, select the cluster heads with unknown nodes at the nearest cluster host terminal and its cluster number. Data clusters arise from the need to find interesting formats
or groups of similar features in a given data set. Using the IWO algorithm, the security and the reliability data are transferred from the source node to the destination which is selected on the basis of the cluster head process. Clustering is a compilation process, so every member of a division has some similarities based on some similarities. A cluster is a set of objects, their similarity or proximity is bundled. A Clustering aim is to collect data/objects in clusters, as each cluster contains similar data. This technique does not contain any information about the cluster or group method, which is why clusters should be included in the supervised study. Cluster complex and linearly indistinguishable data sets, without prior knowledge of the number of groups in nature. Unlike most existing clustering techniques, specific algorithms do not require prior knowledge of the data. In super wide wheels that are wider than other rover wheels, the shape of the profile can significantly change the performance of the drive or reduce side curves with lateral deflection. To get the optimal shape of the wheel with more traction and resist lateral overturning with less torque, following objective functions are defined. The required torque of motor for generating the wheel angular velocity \( \omega \) of nominal magnitude is minimized by the first objective. In the real case the angular velocity \( \omega \) is generated by the torque of motor \( \tau \). The fraction of the real torque and the nominal torque of angular velocity is represented in the first objective function.

\[
D_1 = \left( \frac{|\tau|}{|\omega|} \right) \left( \frac{\tau_m}{\omega_m} \right)^{-1}. \tag{1}
\]

where, \( \tau_m \) denotes the torque of the ideal magnitude. The tractive and torque relation can be denoted by the effective radius of the wheel. The radius of the effective \( s_{\text{eff}} \) is equal to the radius of the wheel average \( s_{\text{ave}} \) in the ideal slip less rigid contact. Thus, the 2nd objective function is,

\[
D_2 = S_{\text{ave}} S_{\text{eff}}^{-1} = S_{\text{ave}} \left( \frac{\tau}{\omega} \right)^{-1}. \tag{2}
\]

The rover platform depends on the third objective. To avoid the slipping of lateral, the force of lateral is used as a parameter when the rover front axis is rotated. The force of lateral resists against the rover steering once the front axis is fixed. Then, the third objective function is,

\[
D_3 = \left( \frac{|g_x|}{|g_d|} \right) \tag{3}
\]
The total function of the objective is defined as sum of these functions as

\[ D_1 = \sum_{j=1}^{3} \psi_j D_j, \] (4)

where, \( \psi_j \) indicates the coefficient of priority which evaluates the significance of the function \( D_j \) in design.

The seeking mode and the tracing mode are the two modes in the behavior of the cat characteristic which is used to solve the different optimization problem. Cats spend a lot of time relaxing, but are always wary of their surroundings in seeking mode.

\[
Y_{i,r} = \begin{cases} 
[1 + (2 \times \text{rand} - 1) \times \text{SRD}] \times Y, & \text{if } D \in n \\
Y, & \text{otherwise}
\end{cases} \] (5)

On updating the values, the equation is

\[ U_{i,r} = z \times U_{i,r} + s_1 \times d_1 \times (Y_{\text{best},r} - Y_{i,r}). \] (6)

The tracing of target is modeled in tracing mode as follows:

\[ Y_{i,r} = Y_{i,r} + U_{i,r}. \] (7)

Calculate the Informative score \( IS_i \) by using the equation,

\[ IS_i = \tilde{\theta}_i \times \log \left( \frac{m_i}{m_h} \right). \] (8)

The working function of cluster formation using cat induced wheel optimization is given in Algorithm 1.

**Algorithm 1.** Cat induced wheel optimization

Input: \( r, \omega, s, g, m \)
Output: \( D_1, IS_i \)

1. Assume the values for the input \( r, \omega, s \)
2. Calculate the first objective function using the \( r \)
3. On substituting the value of \( s \), find \( D_2 \)
4. Overall objective function is calculated using the equation \( D_t = \sum_{j=1}^{3} \psi_j D_j \)
5. Compute the \( U_{i,r} \) and \( Y_{i,r} \)
6. Evaluate the \( IS_i \)

### 4.2 Optimal best path using cuckoo search algorithm

Data can go through many intermediate paths and need to select the best optimal nodes for data transfer. These optimal nodes contribute to the optimal operation of the network. Extensive work has been done to improve the efficiency of network routing and to identify the best route to prevent congestion. There are many techniques for finding optimal path, here we are describing about cuckoo search algorithm. The main function of the router is the best way to send packets. To determine the best path, the router searches its routing list for a network address that matches the packet’s target IP address. The idea of this method is based on the spread of parasites on some cuckoo. There are two instances of cuckoo eggs in other bird cages. The high quality egg nest selected for the new generation coincides with the ability to lay a new egg cuckoo. First, it usually emerges from the nest if it cannot find the first-born cuckoo eggs or extra little birds of the crowd. Second, it fixes and removes the host bird. The Levy plane has an imperative responsibility to explore the given investigate space:

\[
Y_{i,r}^{\text{NEW}} = Y \text{ Best}_j + U_{i,r}^{\text{NEW LEVY}}, \] (9)

\[
U_{i,r}^{\text{NEW LEVY}} = \alpha \times \text{RAND}[0, 1] \times (Y \text{ Best}_j - F \text{ BEST}) \times \text{LEVY}(\beta). \] (10)
Levy flight creates the individual value $j$, where $U_j^{NEW,LEVY}$ is the velocity. The new and best position of the individual $j$ are $Y_j^{NEW}$ and $Y_{BEST,j}$. The value of coefficient range $\alpha$ is 0 and 1. Until the current iteration the current best solution $f_{BEST}$. The distribution coefficient range $\beta$ is of 0 and 3. 1.5 is set to typical. To use the search space described below, the Exotic Egg Detection Technique uses random technology:

$$Y_j^{NEW} = Y_{BEST,j} + U_j^{NEW,RAND,walk},$$

(11)

$$U_j^{NEW,RAND,walk} = RAND(0,1) \times Z(j,:),$$

(12)

By random walk technique the individual $j$ creates the velocity value of $U_j^{NEW,RAND,walk}$. $Z$ is a binary matrix defined by $Z = RAND(C,M)$. The individuals chosen randomly are $Y_{BEST,j}, Y_{BEST,j}$. The below equation describes the solution of candidate in continuous domain:

$$y_j = [y_1, y_2, \ldots, y_C],$$

(13)

where, $y_j$ is the solution ($j = 1, 2, \ldots, M$) in the population. The number of binary bits represents the problem in control variable in the binary version. The following equation represents the candidate solution.

$$y_j = [y_1, y_2, \ldots, y_{M\text{BITS}}].$$

(14)

The below equation determines the dimension of problem, that is, $M_{BITS}$

$$M_{BITS} = M_{BIT} \times C.$$  

(15)

The continuous variable in the double domain is represented by digit of binary bits $M_{BITS}$. Based on the equation, 50% has value 1 and remaining has value 0.

$$y_j = RAND(1,M_{BITS}) \times 0.5.$$  

(16)

When deciding on a binary domain candidate, each person should switch to a nonstop domain to appraise health performance. This revise uses the technique of converting an individual scale binary domain into a continuous domain. The binary domain is represented by $Y$, which determines the quantization value by the following equation.

$$Y_{Quant} = \sum_{n=1}^{M_{BIT}} BIT[n] \times 2^{-n} / \sum_{n=1}^{m} 2^{-n}. $$

(17)

The quantization value of $Y_{Quant}$ in the range of $[0, 1]$. The bit $n = 1, 2, \ldots, BIT_m$ with status BIT[n]. The limits of $(Y_{High} - Y_{Low})$ with continuous domain value of $Y_j$ is calculated as follows:

$$Y_j = Y_{Quant} \times (Y_{High} - Y_{Low}) + Y_{Low}.$$  

(18)

Equations (21)–(23) updates the new position

$$R \left( U_j^{NEW,LEVY} \right) = \text{Transfer function} \left( U_j^{NEW,LEVY} \right),$$

(19)

$$Y_j^{NEW} = \begin{cases} \left( Y_{BEST,j} \right)^{-1}, & \text{if } [0,1] < R \left( U_j^{NEW,LEVY} \right) \\ Y_{BEST,j}, & \text{if } [0,1] \geq R \left( U_j^{NEW,LEVY} \right) \end{cases},$$

(20)

where, transfer function is a transport meaning which maps speed values into likelihood standards. The new and current position are $Y_j^{NEW}$ and $Y_j$. $(Y_j)^{-1}$ is the inverse of $Y_j$. Like the Levy’s aviation system, EPCSA’s discovery of a strange egg creates another new solution for the population.

$$Y_{j,BEST} = [Y_1, Y_2, \ldots, Y_C].$$

(21)
Then, in order to generate new solution approximately the best explanation of all time, you need to configure the existing solution for all control bits starting the worth of 0 to 1 or vice versa.

\[ Y_{\text{BEST}}(j) = [Y_1, Y_2, \ldots, Y_c, \ldots, Y_{\text{NEW}}]. \]  

\[ Y_{\text{NEW}} = [Y_1, Y_2, \ldots, Y_{\text{NEW}}, \ldots, Y_{\text{NEW}}]. \]  

\[ Y_{c, \text{NEW}} = \begin{cases} 1, & \text{if } Y_c = 0 \\ 0, & \text{if } Y_c = 1 \end{cases} \text{ with } c = 1, 2, \ldots, M_{\text{BITS}}. \]  

So far there are two conventional transmission functions with S shaped and V shaped.

\[ R(\text{UNEW}) = 1 / (1 + e^{-\text{UNEW}}). \]  

\[ Y_{\text{NEW}}(j) = \begin{cases} 0, & \text{if } \text{RAND}[0, 1] < R(\text{UNEW}) \\ 1, & \text{if } \text{RAND}[0, 1] < R(\text{UNEW}) \end{cases}. \]  

The control variable position is updated by Equation (20)

\[ R(\text{UNEW}) = \left| \tanh (\text{UNEW}) \right|. \]  

\[ R(\text{UNEW}) = \left| 2 \Pi \arctan \left( \frac{\Pi}{2} \times \text{UNEW} \right) \right|. \]  

The individual position is updated by combining Equations (25) and (26) the position is set by 0 or 1. Therefore, cuckoo search algorithm selects the appropriate transmission function to solve the NR problem (Algorithm 2).

**Algorithm 2. Optimal best path using CSA**

| Input: \(Y_{\text{NEW}}, U_{j, \text{NEW}, \text{LEVY}}\) | Output: \(R(\text{UNEW})\) |
|---|---|
| 1 Initialize cuckoo position and parameters | 7 Return |
| 2 Randomly generate positions and calculate fitness | |
| 3 Compute the position by using \(Y_i = Y_{\text{Qnat} i} \times (Y_{\text{High} i} - Y_{\text{Low} i}) + Y_{\text{Low} i}\) | |
| 4 Update the new position by \(R(\text{UNEW}) = \text{Transfer function}(\text{U}_{\text{NEW,LEVY}})\) | |
| 5 The individual position is calculated by \(R(\text{UNEW}) = 1 / (1 + e^{-\text{UNEW}})\) | |
| 6 Control variable is updated by \(R(\text{UNEW}) = \left| \tanh (\text{UNEW}) \right|\) | |

4.3 Data monitoring coach and player learned neural network (CP-LNN)

Here is a specific training program for coaches and players with intermediate networks. During the training phase, the coach and player networks teach simultaneously with the confirmation system. The major idea of our training program is those coach and player recession networks use similar skin tone beginning communal conversion network so that the player relapse system can simply copy the coaching network. These training programs allow a system of players to maintain excellent performance when they have a limited number of options. On the using the concept of the CP-LNN algorithm the data are monitored in the industrial field and also prevent the accidents using the basic control strategies. Figure 2, at
the end of the transition layers the two network branches are divided into coach and player intermediate network. The fully related coating of the back coach complex is called the T-FC. The associated layer on the player log complex is called STD-FC, which has a 1 to 1 jump and a universal standard pool.

Features are integrated into the coach latency network and the player latency network. Note that the functions of the coach and the player’s intermediate network are encoded with the usual layers of data verification. Completely associated layer play an important role in the FLD complex as the CNN feature makes the map an important strategy. As a result, collective training requires loss target operations, so the STD-FC layer is the D-FC layer. To do this, according to the proposed law, the loss is divided into three functions. The first branch is for the Coaches Regression Network and the next branch is for the Player Regression Network. All network are taught from the end with three loss functions \(M_1, M_2, M_3\). The second loss function \(M_3\) is responsible for reducing the error production of the player’s middle network. The third loss function, \(M_3\), is difference flanked by the loss output vectors T-FC and STD-FC. In preparation, the loss \(M_3\) reflected in all three sub-networks: unit switching network, coach regression network, and player regression network. The three terms of loss terms \((M_1, M_2, M_3)\)

\[
M_1(x, Z_{CNN}, Z_S) = \frac{1}{n} \sum_{j=1}^{n} \| x_j - b(g(y_j Z_{CNN}), Z_S) \|_1, \\
M_2(x, Z_{CNN}, Z_{STD}) = \frac{1}{n} \sum_{j=1}^{n} \| x_j - h(g(y_j Z_{CNN}), Z_{STD}) \|_1, \\
M_3(q, p) = \frac{1}{n} \sum_{j=1}^{n} \| q_j - p_j \|_1.
\]

where, \(n\) is the digit of teaching imagery, \(j\) is the directory of an input picture, \(x_j\) is position fact facial marker organize and \(y_j\) is the input picture. The \(g()\) is the meaning of common problem complex parameterized by \(Z_{CNN}\), \(b()\) is the meaning of the coach regression network parameterized by \(Z_S\), \(g()\) is the occupation of the player regression network parameterized by \(Z_{STD}\). And \(q_j\) is output vector of S-FC and \(p_j\) is that of STD-FC. The Algorithm 3 represents the working function of the coach and player learning neural network.
Algorithm 3. Working function of coach and player learning

Input $y_j, a = 1, \beta = 0, \gamma = 0$
Output $Z_{CNN}, Z, Z_{STD}$

1. For $s = 1$ to $S$ do
2. Feed $y_j$ to shared convolution network: $g(y_j; Z_{CNN})$
3. Feed $g(y_j; Z_{CNN})$ to the coach regression and player regression network: $b(g(y_j; Z_{CNN}) : Z_s), h(g(y_j; Z_{CNN}) : Z_{STD})$
4. Calculate $(M^1, M^2, M^3)$
5. $(Z_{CNN}^*, Z^*, Z_{STD}^*) \leftarrow \text{arg min} \{ aM^1(x, Z_{CNN}, Z_s) + \beta M^2(x, Z_{CNN}, Z_{STD}) + \gamma M^3(q, p) \}$
6. $Z_{CNN} \leftarrow Z_{CNN}^*, Z_s \leftarrow Z_s^*, Z_{STD} \leftarrow Z_{STD}^*$
7. Increase $\beta, \gamma$
8. End

The totality defeat starting the divided point is definite as $M_{\text{branch}} = aM^1 + \beta M^2 + \gamma M^3$. They $a, \beta, \gamma$ indicate the value of all defeat. Because all fatalities influence all network, we will set these settings correctly. Through training, the trainer should be trained regularly as the regression network should perform well. If the coach's intermediate net is not working properly, the player's intermediate net is not working properly. Therefore, we fixed $a = 1$ from opening to end to attain the best presentation. Then, we augment $\beta, \gamma$ from 0 to 1 steadily (i.e., $\beta = \gamma = 1 - e^{-1}$ or $\beta = \gamma = \tan(b(s))$, where $s$ is $s$th epoch), which they shape to the coach and player regression network and communal difficulty network together. If we originally set $\beta = \gamma = 1$, the coach regression network presentation is drenched before it achieves the best presentation. Thus, at the beginning of the preparation, the overall transformation network and coaching network dominate. Once that, the players’ intermediate network is gradually trained.

Algorithm 3 describes the operation of the coach and the player learning model. Indicates the type of in-depth machine training of the neural network when multiple layers of input are used for computer tasks for optimal performance. This means that the data is very constructive and concise. We teach the player the correct knowledge by integrating the knowledge of several coaches to improve accuracy after the abstract. We have optional several authors within the framework of information filtering, the logits vector shaped by the player network for an input video $U_i, i = 1, \ldots, L$ represented by $(A_k)$, where the dimension of vector $(A_k) = [(A_k)_1, \ldots, (A_k)_d]$ is the number of categories $d$. The SOFTMAX layer converts the logits vector $(A_k)$ to a probability distribution $(q_k)_s = [(q_k)_1, \ldots, (q_k)_d]$ describes as,

$$ (q_k)_s = \text{SOFTMAX}(W_s), \quad (32) $$

where

$$ (q_k)_s = \frac{\exp (A_k)_s}{\sum_j \exp (A_k)_j}, \quad \text{for} \quad j = 1, \ldots, d. \quad (33) $$

On the other hand, the logits vector bent by the coach network for an input video $U_i, i = 1, \ldots, L$ is represented by $(A_k)_s$, where the dimension of vector $(A_k) = [(A_k)_1, \ldots, (A_k)_d]$ is the number of categories $d$. By introduce a parameter called warmth, the widespread SOFTMAX layer FSOFTMAX converts the logits $(A_k)_s$ to soft probability distribution $(q_k)_s = [(q_k)_1, \ldots, (q_k)_d]$ describes as,

$$ (q_k)_s = \text{FSOFTMAX}(A_k), s. \quad (34) $$

$$ (q_k)_s = \frac{\text{EXP}(A_k)_s/s}{\sum_j \text{EXP}(A_k)_j/s}, \quad \text{for} \quad j = 1, \ldots, d. \quad (35) $$

The first objective function $W_1$ minimizes the cross entropy with the soft labels $(q_k)_s$, and the soft probability $(q_k)_s$, produced by the player model. $(q_k)_s$ is computed by FSOFTMAX with the same warmth $t$ as the coach model,

$$ (q_k)_s = \text{FSOFTMAX}(A_k), s. \quad (36) $$

where

$$ (q_k)_s = \frac{\exp (A_k)_s/s}{\sum_j \exp (A_k)_j/s}, \quad \text{for} \quad j = 1, \ldots, d. \quad (37) $$

The first objective function \( w_1 \) is

\[
\text{ARGMIN}_M \quad w_1(M) = \text{ARGMIN}_M \left( \frac{1}{L_d} \sum_{i=1}^{L} \sum_{D=1}^{d} (q_s^D_i)^D \ln(q_s^D_i)^D \right),
\]

(38)

where, \((q_s^D)_i^D\), fashioned by the player is the possibility that the \(i\)th video belongs to the \(D\)th class. \((q_s^D)_i^D\) is the soft label shaped by the coach, \(w\) is the weights of the student, \(L\) is the number of teaching videos, and \(d\) is the number of total classes. The second meaning function \( w_2 \) minimize the cross entropy with the hard labels \(Y_{true}\) and the probability \((q_R)_i^D\), fashioned by the student.

\[
\text{ARGMIN}_M \quad w_2(M) = \text{ARGMIN}_M \left( \frac{1}{L_d} \sum_{i=1}^{L} \sum_{D=1}^{d} (y_{true}^D_i)^D \ln(q_s^D_i)^D \right),
\]

(39)

where, \((q_s^D)_i^D\), shaped by the player is the possibility that the \(j\)th video belongs to the \(b\)th class, \((y_{true}^D)_i^D\) is the hard label in sequence, and \((y_{true}^D)_i^D = 1\) if the \(i\)th video belong to the \(D\)th class, otherwise \((y_{true}^D)_i^D = 0\) \(M\) is the weights of the student, \(L\) is the number of training videos, and \(d\) is the number of total classes. The overall objective meaning \(w\) is a prejudiced regular of two diverse purpose function.

\[
\text{ARGMIN}_M \quad w(M) = \text{ARGMIN}_M \lambda w_1 + (1 - \lambda) w_2(M),
\]

(40)

where, \(M\) is the weights of the player and \(\lambda\) is a relative weight.

5 | RESULTS AND DISCUSSION

In this segment, we appraise the planned IoT-HML system with two different test cases are data gathering and data analyzing (for monitoring). The simulations were performed using network simulator for data gathering phase and the anaconda simulator for data monitoring phase. The simulations are carried out with metrics for both proposed protocol and existing. The proposed IoT-HML system with C-IWO based data gathering is evaluate though three different test scenarios are impact of sensor nodes, impact of bad nodes and impact of node movement. The performance of proposed C-IWO based data gathering is compare with the obtainable state of art data gathering technique are cluster based and AODV routing. The different metrics are worn to examine the presentation of proposed steering such as delay, energy consumption, throughput, data delivery ratio, and data loss ratio. The number of sensor nodes randomly placed in the given network size 1200 \(\times\) 900 m\(^2\) and the number of node is taken from 100 to 500 for this analysis. The average mobility of sensor node is 10 mps. For each sensor node, the initial energy is fixed as the 18,720 J. The average transmission range is 50 m. The summary of simulation parameters are given in Table 1.

| Parameters         | Values                  |
|--------------------|-------------------------|
| Network size       | 1200 \(\times\) 900 m\(^2\) |
| Number of nodes    | 50, 100, 150, 200, and 250 |
| MAC type           | IEEE 802_11             |
| Antenna model      | Omni Antenna            |
| Transmission range | 50 m                    |
| Packet size        | 512 bytes               |
| Interference range | 50 m                    |
| Initial energy     | 10 J                    |
| Mobility model     | Random model            |
| Maximum speed      | 10 mps                  |
| Minimum speed      | 1 mps                   |
| Simulation time    | 100 s                   |
5.1 | Performance comparison of data gathering phase

5.1.1 | Impact of node density

In this situation, we differ the digit of nodes as 100, 200, 300, 400, and 500 with the fixed network size as $1200 \times 900$ m$^2$. Figure 3 shows the delay comparison of proposed C-IWO based routing over existing routing protocols are cluster based, AODV. The average delay of proposed C-IWO based routing is 23.2% lower than cluster based routing and 38.4% lower than AODV routing protocol. For 100 sensor nodes, the delay of proposed C-IWO based routing is 10% and 55% for cluster based, AODV correspondingly. Figure 4 shows the energy consumption contrast of planned C-IWO based routing over existing routing protocols are cluster based, AODV. The average energy consumption of planned C-IWO based routing is 14% lower than cluster based routing and 22.8% lower than AODV routing protocol. For 200 sensor nodes, the energy consumption of proposed C-IWO based routing is 15% and 26% for cluster based, AODV correspondingly. Figure 5 shows the Throughput judgment of planned C-IWO based routing over existing routing protocols are cluster based, AODV. The average Throughput of proposed C-IWO based routing is 10.6% higher than cluster based.
For 300 sensor nodes, the Throughput of proposed C-IWO based routing is 18% and 23% for cluster based, AODV, respectively.

Figure 6 shows the Delivery ratio comparison of proposed C-IWO based routing over existing routing protocols are cluster based, AODV. The average Delivery ratio of proposed C-IWO based routing is 1.6% higher than cluster based routing and 6% higher than AODV routing protocol. For 400 sensor nodes, the Delivery ratio of proposed C-IWO based routing is 1% and 2% for cluster based, AODV, respectively. Figure 7 shows the Loss ratio comparison of proposed C-IWO based routing over existing routing protocols are cluster based, AODV. The average Loss ratio of proposed C-IWO based routing is 24% lower than cluster based routing and 34.6% lower than AODV routing protocol. For 500 sensor nodes, the Loss ratio of proposed C-IWO based routing is 52% and 58% for cluster based, AODV, respectively. The summary of comparative analysis of proposed and existing data gathering protocols is given in Table 2.

5.1.2 Impact of bad node density

In this situation, we differ the digit of bad nodes as 10, 20, 30, 40, and 50 with the fixed number of node as 500 and network size as 1200 × 900 m². Figure 8 shows the delay comparison of proposed C-IWO based routing over existing routing protocols are cluster based, AODV. The average delay
FIGURE 7  Loss ratio comparison with nodes

TABLE 2  Comparative analysis of routing protocols over node density

| Nodes | Delay (s) | Energy consumption (mJ) | Throughput (Mbps) | Delivery ratio (%) | Loss ratio (%) |
|-------|-----------|-------------------------|-------------------|-------------------|---------------|
|       | 1         | 2                       | 3                 | 1                 | 2             | 3             | 1       | 2       | 3       |
| 100   | 0.9       | 1                       | 2                 | 11                | 13            | 15            | 48.1    | 39      | 37      | 98     | 97      | 96      | 12      | 25      | 29      |
| 200   | 1.2       | 2                       | 2.3               | 12.9              | 13.5          | 16            | 35      | 32      | 30      | 97     | 96      | 95      | 20      | 29      | 33      |
| 300   | 1.9       | 2.3                     | 2.9               | 13                | 15            | 17            | 34      | 32      | 28      | 95     | 94      | 90      | 25      | 31      | 34      |
| 400   | 2         | 2.9                     | 3                 | 14.2              | 17            | 18            | 30      | 28      | 24      | 90     | 87      | 82      | 29      | 32      | 39      |
| 500   | 2.5       | 3                       | 3.2               | 15                | 19            | 20            | 29      | 25      | 21      | 87     | 80      | 75      | 30      | 33      | 40      |

FIGURE 8  Delay comparison with bad nodes
of proposed C-IWO based routing is 21.4% lower than cluster based routing and 39.6% lower than AODV routing protocol. For 10 sensor nodes, the delay of proposed C-IWO based routing is 23% and 37% for cluster based, AODV correspondingly. Figure 9 shows the energy consumption contrast of planned C-IWO based routing over existing routing protocols are cluster based, AODV. The average energy consumption of proposed C-IWO based routing is 11.8% lower than cluster based routing and 18.2% lower than AODV routing protocol. For 20 sensor nodes, the energy consumption of proposed C-IWO based routing is 17% and 31% for cluster based, AODV correspondingly. Figure 10 shows the Throughput judgment of planned C-IWO based routing over existing routing protocols are cluster based, AODV. The average Throughput of proposed C-IWO based routing is 6% lower than cluster based routing and 15% lower than AODV routing protocol. For 30 sensor nodes, the Throughput of proposed C-IWO based routing is 12% and 21% for cluster based, AODV, respectively. Table 3 depicts the comparative analysis of routing protocols over bad node density.

Figure 11 shows the Delivery ratio comparison of proposed C-IWO based routing over existing routing protocols are cluster based, AODV. The average Delivery ratio of proposed C-IWO based routing is 5.2% higher than cluster based routing and 7.4% higher than AODV routing protocol. For 40 sensor nodes, the Delivery ratio of proposed C-IWO based routing is 11% and 5% for cluster based, AODV, respectively. Figure 12 shows the Loss ratio comparison of proposed C-IWO based routing over existing routing protocols are cluster based, AODV. The average Loss ratio of proposed
TABLE 3  Comparative analysis of routing protocols over bad node density

| Bad nodes | Delay (s) 1 | Delay (s) 2 | Delay (s) 3 | Energy consumption (mJ) 1 | Energy consumption (mJ) 2 | Energy consumption (mJ) 3 | Throughput (Mbps) 1 | Throughput (Mbps) 2 | Throughput (Mbps) 3 | Delivery ratio (%) 1 | Delivery ratio (%) 2 | Delivery ratio (%) 3 | Loss ratio (%) 1 | Loss ratio (%) 2 | Loss ratio (%) 3 |
|-----------|-------------|-------------|-------------|---------------------------|---------------------------|---------------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|----------------|----------------|----------------|
| 10        | 1           | 1.3         | 1.6         | 19                        | 23.1                      | 29.7                      | 54                | 47                | 46                | 90                | 89                | 85                | 15              | 20              | 23              |
| 20        | 1.2         | 1.5         | 1.9         | 25.6                      | 29.7                      | 33.6                      | 47                | 46                | 44                | 89                | 85                | 80                | 20              | 23              | 29              |
| 30        | 1.3         | 1.9         | 2.5         | 29.7                      | 33.6                      | 39.0                      | 46                | 44                | 40                | 85                | 80                | 78                | 23              | 29              | 37              |
| 40        | 1.6         | 2           | 2.9         | 33.6                      | 39.04                     | 41.2                      | 44                | 40                | 38                | 80                | 78                | 75                | 29              | 37              | 38              |
| 50        | 2           | 2.3         | 3           | 39.12                     | 41.23                     | 43                        | 40                | 38                | 35                | 78                | 75                | 71                | 37              | 38              | 47              |

FIGURE 11  Delivery ratio comparison with bad nodes

FIGURE 12  Loss ratio comparison with bad nodes
C-IWO based routing is 16.2% lower than cluster based routing and 29.2% lower than AODV routing protocol. For 50 sensor nodes, the Loss ratio of proposed C-IWO based routing is 25% and 34% for cluster based, AODV, respectively.

5.1.3 Impact of node mobility

In this situation, we differ the speed of nodule as 0.1, 0.2, 0.3, 0.4, and 0.5 with the fixed number of node as 500 and network size as $1200 \times 900 \text{ m}^2$. Figure 13 shows the delay comparison of proposed C-IWO based routing over existing routing protocols are cluster based, AODV. The average delay of proposed C-IWO based routing is 14.4% lower than cluster based routing and 27.4% lower than AODV routing protocol. For 0.2 sensor nodes, the delay of proposed C-IWO based routing is 13% and 31% for cluster based, AODV correspondingly. Figure 14 shows the energy consumption contrast of planned C-IWO based routing over existing routing protocols are cluster based, AODV. The average energy consumption of proposed C-IWO based routing is 12.4% lower than cluster based routing and 22% lower than AODV routing protocol. For 0.4 sensor nodes, the energy consumption
Table 4: Comparative analysis of routing protocols over node speed

| Speed (m/s) | Delay (s) 1 | Energy consumption (mJ) 1 | Throughput (Mbps) 1 | Delivery ratio (%) 1 | Loss ratio (%) 1 | Delay (s) 2 | Energy consumption (mJ) 2 | Throughput (Mbps) 2 | Delivery ratio (%) 2 | Loss ratio (%) 2 | Delay (s) 3 | Energy consumption (mJ) 3 | Throughput (Mbps) 3 | Delivery ratio (%) 3 | Loss ratio (%) 3 |
|-------------|-------------|-------------------------|--------------------|----------------------|------------------|-------------|-------------------------|--------------------|----------------------|------------------|-------------|-------------------------|--------------------|----------------------|------------------|
| 0.2         | 1.3         | 29.5                    | 39                 | 89                   | 15               | 1.5         | 32.9                    | 34.3               | 85                   | 22               | 1.9         | 33.78                   | 39                 | 84                   | 23               |
| 0.4         | 1.5         | 32.9                    | 35                 | 87                   | 16               | 1.9         | 33.78                   | 39                 | 84                   | 23               | 2.3         | 34.12                   | 45                 | 80                   | 29               |
| 0.6         | 1.9         | 33.78                   | 34                 | 85                   | 17               | 2.3         | 34.12                   | 49.3               | 84                   | 29               | 2.5         | 34.12                   | 49.3               | 78                   | 35               |
| 0.8         | 2.3         | 34.12                   | 33.2               | 84                   | 18               | 2.5         | 34.12                   | 49.3               | 78                   | 39               | 3.5         | 34.12                   | 49.3               | 74                   | 43               |
| 1           | 2.5         | 39                     | 30                 | 80                   | 19               | 2.5         | 39                     | 54.2               | 74                   | 37               | 3.5         | 39                     | 54.2               | 70.5                 | 43               |

Figure 15: Throughput comparison with nodes

Figure 16 shows the Delivery ratio judgment of planned C-IWO based routing over existing routing protocols are cluster based, AODV. The average Delivery ratio of proposed C-IWO based routing is 4.6% higher than cluster based routing and 8.6% higher than AODV routing protocol. For 0.8 sensor nodes, the Delivery ratio of proposed C-IWO based routing is 4% and 5% for cluster based, AODV, respectively. Table 4 illustrates the comparative analysis of routing protocols over node speed.

Figure 17 shows the Loss ratio comparison of proposed C-IWO based routing over existing routing protocols are cluster based, AODV. The average Loss ratio of proposed C-IWO based routing is 37% lower than cluster based routing and 47.4% lower than AODV routing protocol. For 1 sensor nodes, the Loss ratio of proposed C-IWO based routing is 31% and 34% for cluster based, AODV, respectively.

5.2 Comparative analysis of data analyzing phase

In this section, we analyze the data monitoring phase with proposed CP-LNN classifier and existing SVM, KNN and DNN classifiers. The values are predicted and statistical measures are taken into account to observe the quality of classifiers. Sensitivity is used to predict whether the given sample is normal or abnormal. When the abnormal is detected it shows that the test is positive, that is, among the total abnormal, it shows the correct amount of positivity.

\[
\frac{t_p}{t_p + f_n}
\]
Specificity is used to predict whether the given sample is normal or abnormal. When the abnormal is absent, it shows that the test is negative, that is, among the total non abnormal and it shows the correct amount of negativity.

\[
\frac{tn}{fn + tn} \quad \text{(42)}
\]

From the confusion matrix, we can obtain \(tp, tn, fp, fn\).

To categorize the affected samples, the accuracy is used to measure the ratio of samples as follows:

\[
\frac{tp + tn}{tp + tn + fp + fn} \quad \text{(43)}
\]

This is the segment to identify the incorrectly categorized samples as abnormal by using the formula,

\[
\frac{fp + fn}{tp + tn + fp + fn} \quad \text{(44)}
\]
TABLE 5 Comparative analysis of data monitoring phase

| S. no. | Parameters (%) | SVM       | KNN       | DNN       | CP-LNN   |
|-------|----------------|-----------|-----------|-----------|----------|
| 1     | Accuracy       | 90.15     | 93.1      | 94.23     | 98.5     |
| 2     | Sensitivity    | 90.39     | 92.5      | 93.5      | 97.3     |
| 3     | Specificity    | 89.78     | 93.91     | 93.78     | 98.2     |
| 4     | Precision      | 89.54     | 94.12     | 95.17     | 98.35    |
| 5     | Recall         | 90.32     | 93.92     | 94.89     | 98.32    |
| 6     | F-measure      | 91.12     | 92.39     | 96.18     | 97.49    |

FIGURE 18 Performance comparison of classifiers

True positive among positive is measured by the precision and calculated by

$$\frac{t_p}{t_p + f_p}$$

(45)

The comparative analysis for classification of the samples was shown in Table 5. It is table obviously depict the performance of planned classifier is very high contrast to obtainable state-of-art classifiers. In addition, the accuracy 98.5%, sensitivity 97.3%, specificity 98.2%, precision 98.35%, recall 98.32%, and F-measure 97.49% of proposed CP-LNN technique is very high compare to obtainable state-of-art classifiers. Figure 18 shows the graphical representation of planned and obtainable classifiers.

5.2.1 Statistical results

For data gathering phase, the average delay of proposed C-IWO based routing protocol is 19.2% and 35% lower than the existing cluster and AODV routing protocols, respectively. The average energy consumption of proposed C-IWO based routing protocol is 12.7% and 21% lower than the existing cluster and AODV routing protocols, respectively. The average throughput of proposed C-IWO based routing protocol is 10.26% and 22.6% higher than the existing cluster and AODV routing protocols, respectively. The average delivery ratio of proposed C-IWO based routing protocol is 3.8% and 7.33% higher than the existing cluster and AODV routing protocols, respectively. The average loss ratio of proposed C-IWO based routing protocol is 16.33% and 3.9% lower than the existing cluster and AODV routing protocols, respectively. For data monitoring phase, we proved the effectiveness of proposed CP-LNN classifier over existing state-of-art classifiers are SVM, KNN and DNN in terms of accuracy, precession, sensitivity, specificity, recall and F-measure.
6 | CONCLUSION

In this research, a hybrid machine learning technique is proposed for IoT enabled industrial monitoring and control system (IoT–HML) to overcome problems in both information security issues with accurate monitoring and control system. Clustering uses the cat induced wheel optimization (C-IWO) method for cluster formation and CH selection. The cuckoo search method computed the optimal path among multiple paths. A CP-LNN monitored the industry and avoid accidents using basic control strategies. The proposed C-IWO-based routing protocol outperformed the existing AODV protocol in terms of 19.2% average delay, 12.7% average energy consumption, 10.26% average throughput, 3.8% average delivery ratio, and 16.33% average loss ratio, respectively. In addition, the proposed CP-LNN technique attained 98.5% accuracy, 97.3% sensitivity, 98.2% specificity, 98.35% precision, 98.32% recall and 97.49% F-measure, they are significantly high compared to state-of-the-art classifiers. This research may be enhanced in the future by analyzing more complicated industrial networks.

CONFLICT OF INTEREST

The authors declare no potential conflict of interest.

DATA AVAILABILITY STATEMENT

Data sharing not applicable to this article as no datasets were generated during the current study.

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How to cite this article: Kota PN, Chandak AS, Patil BP. IOT-HML: A hybrid machine learning technique for IoT enabled industrial monitoring and control system. Concurrency Computat Pract Exper. 2023;35(3):e7458. doi: 10.1002/cpe.7458