Building Cognitive Intelligence In Conveyor Systems using Intermediary Anomaly Detection And Handling (IADH) Technique

Vijaya Ramaraju Poosapati, Vijaya Killu Manda, Vedavathi Katneni

Abstract*: Industry 4.0 is characterized by the interconnection of industrial systems and automation to enable efficient and autonomous industrial operations. Automating the tasks done by humans involves processing a huge volume of data across multiple sources in the industry and incorporating intelligence into the machine from the insights extracted from the processed data. Classification techniques play a vital role in extracting the features and predicting the best possible action that can be taken based on the processed data. However in cases where the underlying business rules changes, the algorithms fail to detect these changes early, thereby impacting the overall accuracy of the model. In this paper, we presented the Intermediary Anomaly Detection and Handling (IADH) algorithm to overcome the problem mentioned above. IADH algorithm will help to quickly identify the changing business rules of the industry and alter the prediction of the model. The architecture of this model does not restrict to one specific industrial machine but enables it to be reusable across multiple industrial systems. The details of the test data collected, algorithm steps, prototype built and software modules built to develop the product with the IADH feature are discussed in this paper. The results of the model with IADH and without IADH are compared to notice the improvements of the proposed IADH Technique for the collected dataset..

Keywords: Industrial Automation, Cognitive Systems, Machine Learning, Classification, Cognitive Automation Software

I. INTRODUCTION

Before improvements in computing power or widespread communication channels, most of the business decisions are driven through expert judgment, these decisions are neither accurate nor reliable, thereby often resulted in unplanned outages in industries due to machine breakdown. But, with the evolution of new technologies like cyber-physical systems, Internet of Things (IoT), Cloud computing and Bigdata, the way decisions are taken to carry out industrial operations changed drastically.

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* Correspondence Author
Vijayaramaraju Poosapati*, Department of Computer Science, GITAM Visakhapatnam, India, Email: vijayaramaraju.poosapati@gmail.com
Vijaya Killu Manda, Department of Computer Science, GITAM Visakhapatnam, India, Email: vedavathi.katneni@gitam.edu
Vedavathi Katneni, Department of Computer Science, GITAM Visakhapatnam, India, Email: mvkillu@gmail.com

The new concept which uses the latest technologies to improve the operations in an industry is referred to as Industry 4.0 and its emphasis more on building smart factories by making most operations autonomous. In typical industrial applications, conveyor systems play a vital role in carrying out day to day operations. They are operated by conveyor belt operators to regulate the speed of the belt. The importance of managing the conveyor belt is often not recognized, but it has a huge impact on overall productivity when it breaks down abruptly as it stops the entire operations in an assembly line or the production unit to which it is connected to. Building an autonomous and reliable conveyor system requires gathering data across the industrial applications and interconnected external systems such as fleet movement, warehouse capacity, and type of material handled. The data of the conveyor system is captured using multiple sensors.
The features in the collected dataset are extracted, and the predicted actions are suggested based on the learning obtained through the training data that is used to build the models. Classification techniques are used to identify the features in the data; however, in scenarios where the business logic changes, the model fails to identify the changes quickly thereby predicts incorrect actions. To overcome this problem, an intermediary algorithm is developed to ensure the business changes are identified and the results suggested by a model are adjusted as per the new business logic change. The objective or contribution of this paper is as follows.

1. A new model Intermediary Anomaly Detection and Handling algorithm are proposed to solve the classification problem in an Industry where business rules change quite often.
2. Choose the better performing classification algorithm, to build the model using IADH on top of selected classification technique
3. Build a configurable software with the proposed algorithm and operate a conveyor belt system prototype on testbed autonomously using the proposed IADH model
4. Conduct tests using the collected dataset to demonstrate the accuracy and efficiency of the IADH model.

II. RELATED WORK

Implementing an intelligent system involves feasibility study to assess the level of automation that can be carried out in the industry. Verheij et al. [1] proposed a measurement model which helps to asses a business process and analyze the level to which it can be operated.

The measurement model suggested by them is dependent on three high-level parameters such as complexity of work, data quality and capability of the automation. The strategy implemented in enabling intelligence, plays an important role in making the process successful, Mattsson et al.

[2] proposed a standard cognitive strategy for a successful implementation by following three steps, they are 1. Selecting the assemble mode, 2. Choosing the automation carrier and 3. Content of intelligent Automation. Fasth et al. [3] Discussed the human interaction to find central factors and trends in intelligent automation which will be used to suggest intelligent automation strategies. Once the strategy is defined, identifying the best possible area to implement automation for maximum ROI is important, Panigari et al. [4] used Kanban method to identify the highest defects in a production environment, which are best suited for intelligent automation implementations. Automation in an industry can be physical and intelligent, Fasth et al. [5] provided intelligent automation case studies using DYNAMO ++ methodology in automotive industry to improve the use of intelligent automation.

In an environment where human and machine interacts, due to lack of ability of cooperation lot of serious deficiencies would happen in a complex environment to overcome this Putzer[6] et al. proposed a generic intelligent system architecture based on a cognitive model of human behavior to achieve widespread intelligent applications. Onken et al. [7] developed a framework for automating the function of the industry called Cognitive systems Architecture (COSA), which emphasis on capturing the context of the data to carry out and monitor operator actions. To implement intelligent automation successfully, data from all industrial applications has to be collected. Martins Sampaio et al. [8] discussed the challenges of collecting data from multiple complex systems and the process of decision making in a complex industrial environment and how business logic changes impacts the learning of the model. Essa et al. [9] used machine learning, and big data processing to inspect industrial products in a fast and effective way using neighborhood maintaining approach. Burns et al. [12] discussed modeling automation along with intelligent work analysis to assist the process of human-automation and coordination between human and machines in a complex industrial environment. Cho et al. [13] discussed the data gathering techniques by use of IoT and developed a hybrid Machine Learning approach which can be used in industries for predictive analysis.

Various intelligent automation is built using the architecture, strategy, and technologies discussed above, Gerhard Zucker et al. [14] developed an intelligent system for energy management of a building by using knowledge base and explained the methodology and algorithms which are used to implement the logic. They applied the proposed model on building to automate the operations of HVAC operations. V. M. Nivas et al., [16] developed an automated guided trolley which is preloaded with the industrial operational and constructional maps. By using GPS and computer vision techniques, the autonomous trolley can sense the environment and help in navigating in an industry. Czubenko, M et al. [18] proposed an autonomous driving car using techniques with few assumptions to mimic human behavior. The process involved in decision making of a system while driving a vehicle is detailed by using intelligent decision-making system process. M. L. Alvarez et al., [19] presented a methodological approach to design and develop control software for a complex industrial system by relying on Model-Driven Engineering (MDE) which adds flexibility during design. A Proof of Concept (POC) is built and tested on medium complexity projects, and the impact of the model is tested. J. Frost et al., [21] proposed new computer architecture to enable intelligent systems using a Street Engine which uses highly parallel computer architecture specifically designed for processing huge volume of data faster and enable cognition in industrial systems

III. PROPOSED MODEL

Building an intelligent cognitive system involves an approach in which the knowledge part is separated in knowledge processing to determine the actions that are to be taken by the system. The actions suggested are often considered as the best possible action based on the observations in training data that was used in building an intelligent system. Hence the quality of the dataset plays a vital role in determining the accuracy of the model. The dataset used in this paper is a combination of both sensor data collected from conveyor system and the data from industrial systems such as SCADA, ERP and EAM, which gives information about the external factors in the industry which has considerable impact on the kind of action to be taken by the operator who is operating the conveyor belt. The model proposed in this paper uses two levels of data processing to suggest the action, in the first level, by using classification techniques, the model tries to detect the patterns, identify the features and suggests/predicts a possible action. In the second level, the proposed Intermediary Anomaly Detection and Handling (IADH) algorithm compares the action predicted by first level with the value stored in the class of the data record and alters the decision suggested if the counter (Incremental Value) percentage is less than the predefined limit (constant).

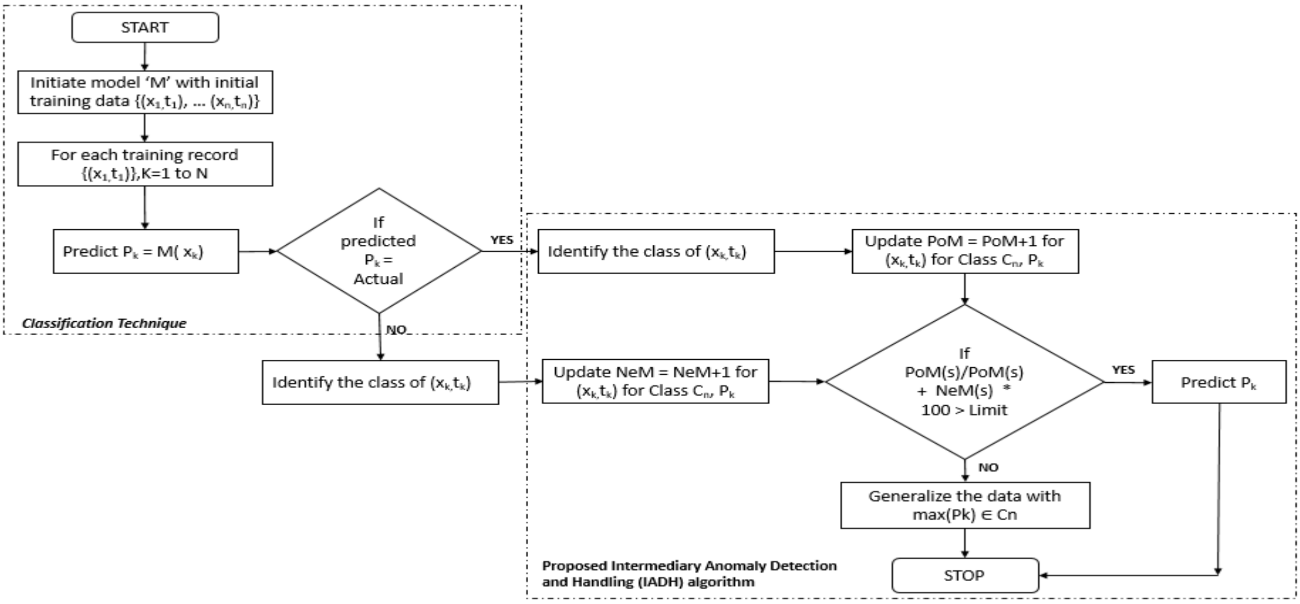

Figure 01: High-level process involved in Model

The Intermediary Anomaly Detection and Handling algorithm play a significant role in improving the decision taken by the first level, by detecting business logic changes in the data early and thereby avoiding incorrect suggestions.

i. Data Collection & Pre-processing:

Data is collected from industrial information systems using sensors, IoT devices & communication channels which gather huge volume of data, The dataset contains, various parameters related to conveyor belt system and internal industrial data, there are 52 columns which give information about the condition of the conveyor belt such as vibration, temperature, sound, and pressure from six different locations of the belt and spindle. The actions like the speed level of the conveyor belt set by the operator for a specific data set are captured to train the model. The dataset contains 19853 records, out of which 13235(66%) records are used to determine the best classification algorithm for the collected dataset. To validate the performance of 3500 (18%) records are used. The proposed model performance is evaluated using the remaining 3118 (15%) records to evaluate and compare the performance of proposed IADH technique against the classification algorithm.

ii. Classification Selection:

Classification algorithms are used to categorize the data into multiple and distinct classes which can help to identify the features in the dataset. The performance of these algorithms varies depending upon the data, so the best suitable classification algorithm for the current dataset is selected based on Efficiency metrics (Accuracy, Precision, Recall & F1 Score). We considered few most widely used classification techniques like Decision Tree, Gaussian Naïve Bayes, K Nearest Neighbours, Linear Discriminant Analysis, Logistic Regression, Random Forest and Support Vector Machine and evaluated its performance using Scikit learn libraries, which are built using python language. The Scikit learn is an open-source software, which is built for data mining and data analysis.

The Accuracy, Precision, Recall and F1-score of the classification algorithms are calculated based on the confusion matrix which can be used to determine True Positive (TP), True Negatives (TN), False Positives (FP) and False Negative (FN) in the dataset for each of the class. The current dataset has 3 classes namely 1, 2, 3 each denoting the speed level of the conveyor belt in which it is operated. The following are the formulas used to calculate the Accuracy, Precision, Recall, and F1-Score.

$$\text{Accuracy} = \frac{TP+FN}{TP+FN+TN+FP}$$

$$\text{Precision} = \frac{TP}{TP+FP}$$

$$\text{Recall} = \frac{TP}{TP+FN}$$

$$\text{F1 Score} = \frac{2(Precision)(Recall)}{Precision+Recall}$$

Here in the current dataset as we have 3 classes (Class 1, Class 2 and Class 3), the actual accuracy, precision, recall, and F1 Score are calculated based on the average of all the class in the confusion matrix (3 * 3). The results of the classification algorithms trained with 13237 (66 %) records and tested with 3500 (18%) records are as follows.

	Accuracy	**Precision**	**Recall**	**F1-Score**
DT	68.43	69.64	74.73	65.05
GNB	67.94	69.94	67.76	58.63
KNN	42.31	45.85	42.95	39.37
LD	67.97	69.98	74.12	64.64
LR	**70.14**	**70.41**	**75.11**	**66.28**
RF	67.51	69.61	75.12	64.42
SVM	65.54	69.29	72.85	62.74

Table 01: Classification Algorithms – Selection Process

Based on the above results, it is evident that the Logistic Regression classification algorithm performed consistently above other algorithms in Accuracy, Precision, and F1 Score, whereas Random forest scored slightly above Logistic regression in Recall value. So, Logistic regression is considered for building the proposed model.

iii. Preliminary overview of the model

For the collected dataset, Logistic regression algorithm is selected to classify the given dataset, which contains multiple results (1, 2, 3) which are the actions taken by human on the conveyor system. So, we used multinomial logistic regression techniques as a base algorithm to predict the possible action.

The logistic function or a sigmoid function is defined as

$\sigma(r) = e^t / (e^t + 1) \Rightarrow 1/(1+e^{-t})$, where $t = \beta_1 + \beta_2 x + \beta_3 x$ for the given set of 3 values in the collected data set.

The generalized logistic function can be represented as

p: R -> (1, 2, 3) as

$p(x) = \sigma(r) = 1 / (1 + e^{-(\beta1 + \beta2x + \beta3 x)})$

The inverse of the function is defined as

$g(p(x)) = \sigma^{-1}(p(x)) =$

$\text{logit } p(x) = \left(\frac{P(x)}{1+P(x)}\right) = \beta_1 + \beta_2 x + \beta_3 x$

Here 'g' is a logistic function, 'ln' is a natural algorithm, 'p(x)' is the probability of the dependent variable, β_1 is the intercept, $\beta_2 x$ and $\beta_3 x$ are the coefficient and base 'e' is the exponential function.

iv. Proposed Intermediary Anomaly Detection and Handling (IADH) Algorithm

IADH algorithm is developed with the objective to detect the changes in industrial data much earlier than classification algorithms thereby improving the accuracy of the overall model. The values of 't' and 's' are passed on to the algorithms as constants which can be determined based on the industry and complexity involved in the process. Following are the steps.

- Collect data for all relevant industrial sensors independently. $X = \{x_1, x_2, x_3 \ldots X_n\}$ and map the actions taken
- Generate classes $C_1, C_2 .. C_n$ based on sensors data & business data
- Generate distance-based variance and sequence-based variance
- Define constant 't' for tolerance and 's' for the sample size to calculate the tolerance level
- At each action, the parameter (x, y, p_k, a) is checked, where 'x' is the current state before the action taken, 'y' is the state after the action, 'p_k' is suggested action, 'a' is the appropriate action to be taken.
- For each records in the dataset, Repeat the following
  - For all X, where $p_k = a$, Identify the class C_n and update the count of
    $C_n (p_k)$ (PoM) as PoM = PoM + 1, where PoM is the Positive Match
  - For all X, where p_k != a, , Identify the class C_n and update the count of
    $C_n (p_k)$ (NeM) as NeM = NeM + 1, where NeM is the Negative Match
- For each $C_n (p_k)$
  - If PoM(s)/[PoM(s) + NeM(s)] *100 > t,
    - Revisit the rules with matching criteria (C_n, p_k,a) and generalize the rule criteria for each 'p_k' that belongs to C_n
    - Update the recommendation p_k to max value in $C_n (p_k)$
    - Reset PoM(s) and NeM(S)

    else $p_k = p_k$ (No change in prediction)
- End

Diagrammatic Representation:

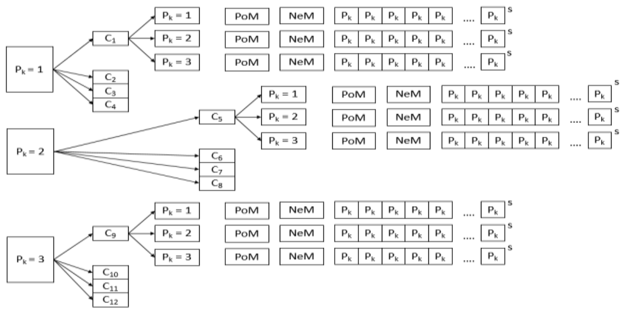

Figure 02 – IADH Algorithm representation for the dataset

IV. EXPERIMENTAL SETUP

To demonstrate the performance of the proposed Intermediary Anomaly Detection and Handling technique, an S/W is built along with the conveyor belt system prototype. The conveyor system can be operated and controlled by S/W in three different speed levels (1, 2, and 3). The entire setup is categorized into 2 parts. 1. Hardware setup to build a conveyor system prototype 2. Software application to automatically control the conveyor system without human intervention.

i. Building a Conveyor System

A conveyor is built using multiple pulleys with a continuous loop of material, often referred to as a conveyor belt. The conveyor system is powered using electricity, which rotates the pulley thereby making the belt attached to a pulley to move forward. The pulley which is connected to electricity and is moving is called drive pulley, and the pulley which is not powered is called idler. With the continuous loop of belt attached to the pulley, the material placed on it moves ahead allowing the transport of material.

There can be many types of conveyors in the industry like flat belt conveyors, blanket belt conveyors, and troughed belt conveyors and for prototype purposes, we have used flat belt conveyors as shown below.

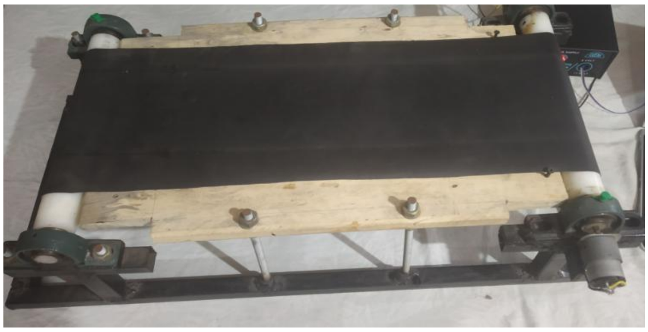

Figure 03: Mechanism of Belt Conveyor

Belt, Tension roller, Drive Roller and Idler Roller (Below the belt to support the conveyor belt system) are the key components in a conveyor system. Other components used to assemble the conveyor system are listed below

DC Motor: A DC motor helps to covert a direct current into mechanical energy which helps pulley to rotate. It contains a magnetic coil through which the electric current is passed, and the magnetic force is generated that produces a torque in the motor

Microcontroller: These are often used as a general-purpose processor which accepts specific pre-programmed inputs and processes it to provide specific output. They contain a specific volume of RAM, CPU along with the number of input and output ports which helps in receiving and sending the inputs and processed output. We have used an AT89C51 model of microprocessor to communicate between hardware (conveyor belt) and software.

Crystal Oscillator: Crystal oscillators are used in a microcontroller to produce electrical signals with pre-programmed frequency by utilizing vibrating crystal mechanical resonance. A quartz crystal is used in the oscillator.

Diode: A Diode is part of a crystal Oscillator, it is operated in a specific range of voltage, allows only a unidirectional flow of current. It blocks current in a reverse direction while reverse voltage is within a limited range.

Integrated Circuit: L293D is the model used in this prototype, which is an h-bridge motor, as the device takes low voltage of current, these IC acts as an amplifier to provide a higher current signal. They contain two inbuilt H bridge circuit drivers, and it helps to operate two DC motors in two different directions.

Max232: It was designed by Maxim and is widely used for communication in RS232 systems. It helps to convert the Transistor-Transistor logic to RS232 understandable level signal. As there are multiple signal modes used in the prototype Max232 plays an important role in transferring the data to different signal level waveforms.

Transformer: Transformer helps to transfer AC from one circuit to the other at a constant frequency. The voltage of the power can be altered depending upon the requirement.

ii. Software building with IADH Technique

Open-Source software is built with IADH technique to control conveyor belt system autonomously and effectively without any human intervention. The software can be reused with other machines by changing the parameters depending on the business needs in configurations. Following s/w tools are used to build the software.

Database: MariaDB, Version 10.3, Frontend: Angular 7, Backend: Node JS 11.9.0

Design: HTML 5, CSS 3, JavaScript 1.8.5, Data Analysis Tool: Scikit-Learn, Version 0.20.2.

Scripting: Python, version 3.7.2, Operating System: Windows 10.

The functionality of the Software:

The overall functionality of the S/W is divided into 3 modules, each performing a specific task. The modules are

i. Admin configurations
ii. Operator console
iii. Feedback

i. Admin Configurations:

The settings of the IADH algorithm can be configured here depending upon the kind of machine being automated, or the kind of complexity involved in an industry where this software is being used. The settings that can be changed in the S/W are

Tolerance Level: Tolerance level (t) is set and used when the system is running in an autonomous mode. If the tolerance level is set as 10% , then the model would predict the same value as suggested by the level 1 algorithm as long as the PoM in ‘s’ is more than 90%

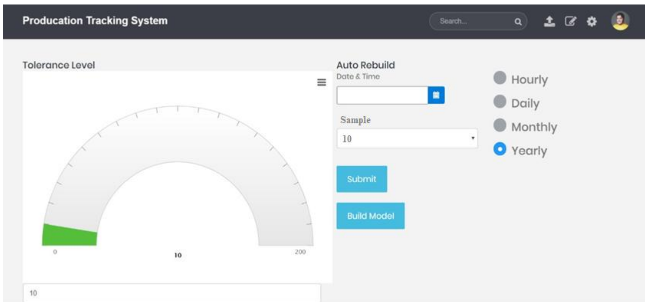

Figure 04: Configuration Setting in S/W

Sample Size: Depending upon the volatility of the industry, the sample set is selected, which would be considered as a base to identify the frequently changing business rules of the industry.

Auto Rebuild: The frequency at which the model rebuild to be done can be configured. It can be set by Day, Week, Month, or Year as per the need of the business. This would allow the model to rebuild and improve the accuracy based on the learning from feedback during the operations

ii. Operator Console:

Cognitive Intelligent S/W is operated in 3 different modes depending upon the maturity of the model and its accuracy. Initially, it is operated in Manual mode, where the operator can view the suggestion given by the software and take action manually depending upon his/her judgment. In semi-auto, the suggestion is given by the Software, and it waits for preconfigured seconds before controlling the conveyor system autonomously with the action predicted by the software. During the wait time, the operator can alter the decision suggested by the S/W. The other mode of operation is Auto, in which the entire machine is controlled autonomously without any human intervention.

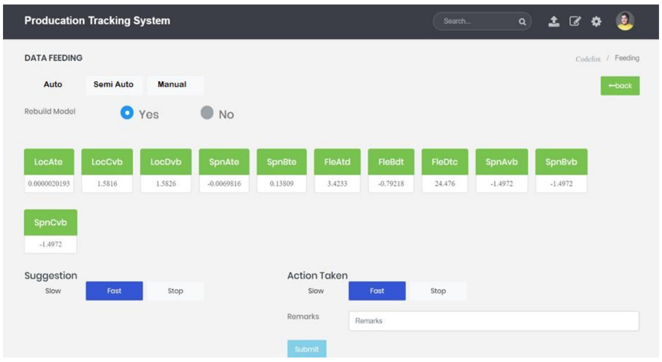

Figure 05: Operator Console Screen

The suggested action by the S/W is displayed, the action taken and the remarks entered by the operator are stored for relearning.

iii. Feedback for Learning

All the decisions taken through the system are reviewed to enable continuous learning. The review mechanism can be automated if the resultant of the action is fixed and can be measured automatically. While in case where the result of the decision varies and cannot be automatically acknowledged, a manual process to mark the wrong decision is provided on this screen.

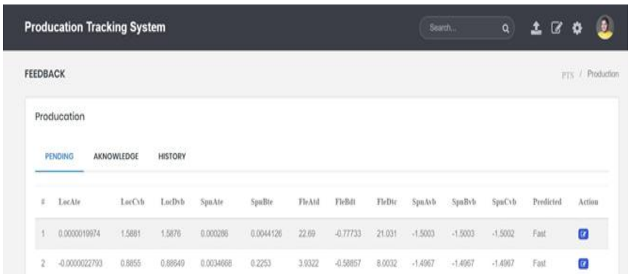

Figure 06: Operator Console Screen

The acknowledged review feedback is fed to the model for relearning. This mechanism helps to improve the accuracy of the model to a great extent over a period of time. For all the modules independent login is provided to ensure that all the functions of configuring, using and providing feedback are done by respective authorities in an industrial system.

iii. Experiments:

In this section, a series of experiments are conducted to evaluate the efficiency and accuracy of the proposed IADH algorithm; the experiments are carried on a server with windows 10 Operating system, Intel Core i7, 3.2 GHz, and 8 GB RAM. The S/W is loaded in the system, and the test data is passed to the S/W to evaluate the performance of the model. The S/W is connected to the built conveyor system.

The dataset used in this paper is collected from an Indian logistics company, and the data is being used with permission for research purpose only. The dataset contains 19K + records collected from various operations spanned across 18 months from Jan 2017 to June 2018. The dataset contains 52 attributes; the data is scaled processed without any null values. Feature selection on the dataset is made by using the techniques proposed by Nie et al. [refer] via $l_{2,\ 1}$ norms minimization, The data in the dataset contains data of sensors from 6 different locations mentioned as A,B,C,D,E,& F, and at each location temperature, pressure, vibration, accelerometer data is collected from the belt and the spindles attached to the conveyor system. Feature selection is run with multiple combinations such as, without location A, Without location B, Without location C and so on, we also considered the industry data such as fleet distance, type of material transported and volume of the container used for loading or unloading as few key parameters. Below are the results of key feature extraction step.

Table 02: Key feature identification table – 1

	Except for Location A	Except for Location B	Except for Location C
Accuracy	64.51	64.28	65.88
Precision	65.16	65.73	66.22
Recall	67.41	67.13	66.67
F1 Score	61.37	61.16	62.93

Table 03: Key feature identification table – 2

	Except for location D	Except for Location E
Accuracy	65.42	64.54
Precision	63.94	64.16
Recall	64.3	64.56
F1 Score	62.39	61.26

Table 04: Key feature identification table – 1

	Except for Location F	Without G
Accuracy	63.14	56.62
Precision	62.63	56.45
Recall	62.62	55.16
F1 Score	59.94	54.47

Table 05: Key feature identification table – 2

	Without L	Without V	Complete Data
Accuracy	60.34	59.37	70.14
Precision	60.12	58.85	70.4
Recall	59.46	58.38	75.1
F1 Score	57.74	56.85	66.27

Based on running isolated test, it clearly shows Attribute G, L and V have a significant impact on the overall accuracy of the model, whereas the data from multiple locations has impact, but little less than G, L, and V Values. Therefore, entire data is used to run the model for better accuracy.

V. Results & Conclusion

To validate the performance of the Intermediary Anomaly Detection and Handling (IADH) algorithm, the performance of the model with IADH is compared with the model without IADH. As we have selected Logistic regression as a base algorithm for the dataset under consideration, we compare the proposed model with Logistic Regression using the validation dataset with 3318 records. Both the models are trained with 16735 records. Below is the performance of Logistic regression model.

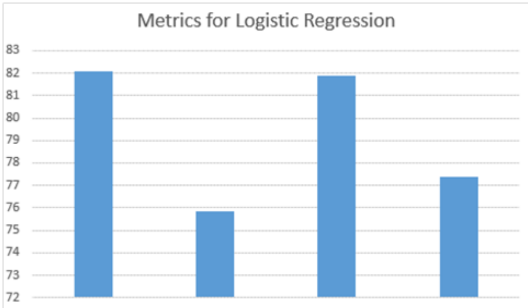

Figure 07: Logistic regression results and confusion matrix

For the logistic regression algorithm, accuracy is around 82.07, precision is 75.84, Recall is 81.88, and F1 Score is 77.36 as displayed pictorially in above figure 3. It is noticed that the efficiency of the logistic regression algorithm increased with more data, in our initial comparison in Table 01, with 13237 records, the accuracy of the algorithm was only 70.14, whereas with 16735 records it is increased to 82.07.

For our proposed model with IDAH techniques, we have evaluated the performance using the built software. The confusion matrix for the model is shown below.

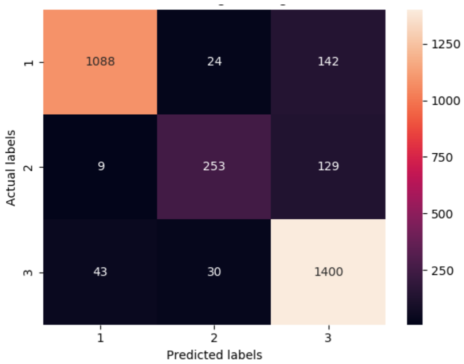

Figure 08: Confusion Matrix of IDAH algorithm

The Accuracy, Precision, Recall, and F1 score are calculated based on the True Positives (TP), False Negatives (FN), True Negative (TN) and False Positive (FP). In the current dataset as we have 3 classes, the confusion matrix has to be clearly understood to calculate the efficiency metrics of the proposed model.

The TP, FP, FN, and TN can be calculated, based on the below table. The calculations are to be done separately for each of the class, and the average of all the class is considered for calculating the efficiency metrics.

For Class 1:

Table 06: Class 1 – Representation

	Class 1	**Class 2**	**Class 3**
Class 1	**TP**	**FN**	**FN**
Class 2	**FP**	TN	TN
Class 3	**FP**	TN	TN

For Class 2:

Table 07: Class 2 Representation

	Class 1	**Class 2**	**Class 3**
Class 1	TN	**FP**	TN
Class 2	**FN**	**TP**	**FN**
Class 3	TN	**FP**	TN

For Class 3:

Table 08: Class 3 Representation

	Class 1	**Class 2**	**Class 3**
Class 1	TN	TN	**FP**
Class 2	TN	TN	**FP**
Class 3	**FN**	**FN**	**TP**

Based on the above tables, TP, FN, TN and FP values of the individual classes are calculated; below are the results.

Table 09: Test dataset results on 13237 records

	TP	**FN**	**TN**	**FP**
Class 1	1088	52	1812	166
Class 2	253	54	2673	138
Class 3	1400	271	1374	73

The objective of any model is to reduce the number of false negatives and false positives so that the overall accuracy of the model increases. Accuracy, Precision, Recall, and F1 Score of the model are calculated by the average of all three classes in the dataset. The IDAH model efficiency metrics are as follows.

Table 10: Test dataset results on 13237 records

	Accuracy	**Precision**	**Recall**	**F1-Score**
IDAH Model	87.9	87.21	82.17	84.14

Also, along with the above-mentioned metrics, True Positive Rate, True negative rate, False Positive rate, and False Negative rate can be calculated using the values returned by the confusion matrix.

True positive Rate (TPR) = $\frac{TP}{TP+FN}$

False Negative Rate (FNR) = $\frac{FN}{FN+TP}$ (or) 1 – TPR

True Negative Rate (TNR) = $\frac{TN}{TN+FP}$,

False Positive Rate (FPR) = $\frac{FP}{FP+TN}$ (or) 1 – TNR

Using the above formulas, the AM, BA, TPR, FNR, TNR and FPR metrics for the given test dataset are as follows.

Table 11: Other Metrics for IADH

	TPR	FNR	TNR	FPR
IDAH Model	82.17	17.82	92.91	7.09

In comparison with Logistic regression model, the proposed model with IADH performed consistently well and successful in detecting the changes in the business rule early and adapting to the new changes much faster than the traditional Logistic regression model. The comparison of efficiency matrix is given below. In all the key parameters, IADH algorithm is consistently ahead of Logistic regression.

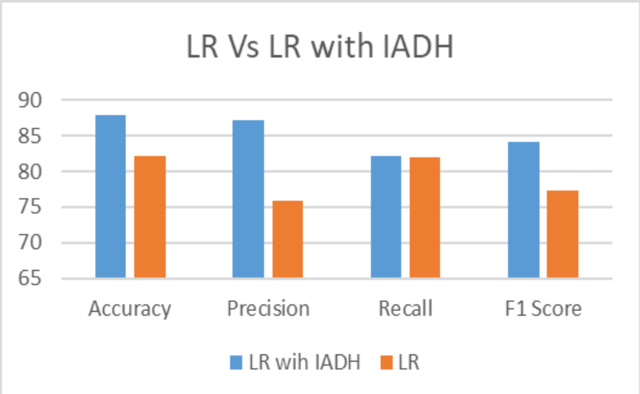

Figure 09: Comparison of LR vs. Proposed Model with IADH Technique

Learning Rate Comparison and Improvements:

Table 10: Other Metrics for IADH

	LR (Standalone)	Proposed Model	Improvement %
Accuracy	82.07	**87.97**	**7.18**
Precision	75.84	**87.21**	**14.99**
Recall	81.88	**82.17**	**0.35**
F1 Score	77.36	**84.14**	**8.76**

Accuracy, Precision, and F1 Score of the model with IADH increased considerably and was able to predict more accurate results when compared to the standalone logistic regression model.

VI. CONCLUSION

Building intelligent industrial systems play a vital role in improving the overall productivity of the industry; however, the model used for building intelligence should be able to quickly detect the changes in the pattern and adjust itself to ensure appropriate decision is suggested by the model. The proposed Intermediary Anomaly Detection and Handling technique is able to detect the pattern changes quickly and alters the suggestion given by the traditional algorithm, thereby improving the overall productivity of the algorithm. Based on the tests conducted and the results it is evident that the proposed IADH technique can learn quickly and provide suggestion with greater accuracy than traditional standalone algorithms. The proposed technique can further be used in other industrial machines to build autonomous systems and monitor its results, depending upon the results and consistency the S/W built to control can be operated in autonomous mode, where the entire operations can be carried out without any human interventions.

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AUTHORS PROFILE

VijayaRamaraju Poosapati is a research scholar on Cognitive Studies in Industrial Automation at GITAM Deemed to be University, Visakhapatnam. He is a PMI certified project manager and a Six Sigma black belt certified. He worked as a Sr. project manager for one of the top services company in India, and was responsible for driving Automations for few of the top Fortune 500 companies. He received many accolades for his automation initiatives, and his work was recognized as the best automation initiative of the year. He holds a master's degree in computer applications (MCA) from Sikkim Manipal University. His previous research work involves building smart industrial machines using cognitive intelligence.

Vijaya Killu Manda is a Research Scholar at the Department of Computer Science in GITAM Deemed to be University, Visakhapatnam. He is a Technical Architect for an IoT based automation company. His areas of research interest include Machine Learning and Blockchain technologies. He authored several technical and research papers of international repute in those areas. He holds a Masters degree in Computer Applications (MCA), Masters in Business Administration (MBA), and a Bachelor degree in Law (LL.B).

Prof. Vedavathi Katneni Prof. Vedavathi Katneni is presently working as Head of the Department, Computer Science Department, GITAM, Visakhapatnam. She is a life member of Indian Society of Technical Education, Computer society of India and Indian Science congress association. She completed her Ph.D. from Andhra University, Visakhapatnam. During her current tenure at GITAM, she was awarded multiple awards from women empowerment cell of GITAM for her contribution towards empowering women and initiatives taken towards empowerment.