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Decision Support System based on Industry 5.0 in Artificial Intelligence

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Abstract: The term "Industry 5.0" was created to address personalized production and the empowerment of humans in manufacturing processes, as Industry 4.0 was unable to meet the increasing need for customization. There are differing opinions about what Industry 5.0 is and what comprises the reconciliation of humans and robots from the term's inception. A new "proof of concept" for enhanced Process Mining is to be adopted to automate decision-making, optimize machine settings, and conduct maintenance interventions to provide a novel method for modeling production management in industry. Both supervised and unsupervised artificial intelligence techniques are incorporated into the PM model's complex electrical sensing and actuation subsystems. These systems facilitate intelligent decision-making by suggesting theoretical process workflows that are powered by a Decision Support System (DSS) engine. By solving these identified obstacles, future researchers may enhance the decision assistance systems. Every decision support system is subjected to a methodical analysis. An extensive assessment is carried out considering many factors such as compatibility, expandability, ease of use, and so on. Future issues are identified and outlined based on the evaluation's findings, which also reveal development trends and offer suggestions for future research directions.

Keywords: *Process Mining (PM); Decision Support System; industry 5.0; Artificial Intelligence*

1. Introduction

Due to the introduction of Artificial Intelligence (AI)-based solutions and rapidly expanding digital technologies, the industrial sector is currently undergoing a rapid shift. Increasing productivity while maintaining human involvement in the manufacturing process is an issue addressed by manufacturers worldwide. The increasing importance of robots in the manufacturing process due to the development of upcoming technologies like brain-machine interfaces and artificial intelligence makes this work much more challenging. The upcoming Industrial 5.0 revolution has the potential to tackle these issues [1]. To put it briefly, Industry 5.0 envisions people and robots cooperating instead of competing with one another. This revolution preceded Industry 2.0, Industry 3.0, Industry 4.0, and Industry 1.0.

Industry 1.0 first appeared in the eighteenth century, which was centered on the industries of extraction, transport, paper, glass, and clothing, and electricity from steam, metals, tools, concrete, chemicals, and gas. Transportation, employment, agricultural expansion, and steady growth are among the benefits of this revolution. Industry 1.0 is related to several downsides, such as pollution and implementation time required for associated processes. Geometry and linear programming were two mathematical tools used in Industry 1.0. Beginning in the 1800s, Industry 2.0 concentrated on the following areas: plastic, bikes, automobiles, fertilizer, practical science, generators, turbines, telecommunications, paper, steel, rail, electricity, paper, petroleum, chemical, and maritime technology. The invention of combustion engines, cell phones, the postal system, and the power grid are among the innovations of this revolution. Industry 2.0's biggest flaw is how expensive it is to use electricity. Industry 2.0 made use of geometry, differential equations, and linear equations as exact tools. The main issue with Industry 3.0 is that some scenarios will prevent automated systems from functioning. For instance, putting Flexible Manufacturing Systems into practise was one of Industry 3.0's main goals. These solutions, however, came with additional operational costs and were too complicated for some organizations to afford. Many businesses were put off by the intricacy and additional expenses.

The mathematical techniques of linear programming, logical controllers, and differential equations were used in Industry 3.0. The 21st century saw the emergence of Industry 4.0, which was centred on all sectors using intelligent systems. The fourth industrial revolution will benefit from machine learning, which is

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contributing to the development of completely automated and artificially intelligent systems that can function in unpredictable environments. The potential for unprotected cloud data and the lack of fully built industry-specific expert systems are the two disadvantages of Industry 4.0. Network theory and optimization strategies are two of the mathematical instruments used by Industry 4.0. The BPMN approach is used to apply PM in multiple application domains and to "explode" in the "proof of concept" of the theoretical model shown in Figure 1.1.

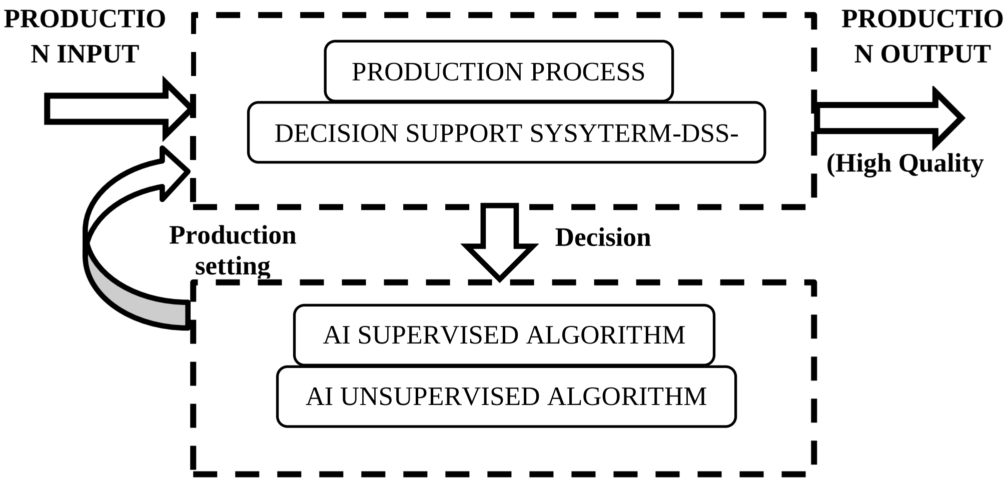

Fig. 1.1. The PM's "proof of concept"

Making decisions that will affect their communities for a long time is difficult for decision-makers in the current environment of tightened environmental rules, a growing emphasis on equitable growth, and the shift towards circular economies [2]. Several alternatives and different sources of uncertainty must be taken into account when making such judgments, which frequently call for compromises on social, economic, technical, and environmental considerations. Because of this, making decisions becomes extremely difficult, necessitating the usage of specialist tools like DSSs to assist in handling these scenarios.

Decision Support Systems are designed to help decision-makers handle situations in which there are several possible solutions to an issue, none of which is objectively superior to the others; instead, the choice of an alternative is determined by the decision-makers preferences. These systems are capable of helping to structure and resolve contentious issues, as well as enhancing decision-making transparency, giving users a better grasp of the problem scenario, and encouraging learning. They are more than just decision trees, designs, and evaluations, for instance. As a result, DSSs address special issues about the process of choice that are not encountered in conventional models or system development.

This is how the remainder of the paper is organised: The procedure for gathering data, including the databases from which it is extracted and examined, is covered in Section 2; the results of the text mining technique used are discussed in Sections 3 and 4; the paper is concluded and the contributors are listed in Section 5.

2. Literature Review

Zhai, Z., et.al [3] A different business called Prosper uses cloud computing, AI, and using computer vision to develop a digital agricultural system that helps farmers analyse data collected from their farms, complementing IBM and the Agriculture 4.0 effort. This system can monitor crop growth rates and recommend the optimal times for fertilization, water supply, pollination, and harvesting. Notification about crop illnesses might also be sent to farmers. Based on Prospero's statistics, production yield may be projected with 95% accuracy, and productivity can grow by up to 30%.

Sutton, R. T., et.al [4] The "Personal Health Record" (PHR) has allowed for the integration of CDS capabilities, much like EHRs, with the patient acting as the data's "manager" or ultimate user. The implementation of shared decision-making between the patient and the physician is best facilitated by CDS-supported PHRs, as CDSS can eliminate the obstacle of "lack of information" that prevents patients from taking an active role in their care. This is a major step towards patient-focused care.74% of PHRs can be standalone web- or mobile-based programs, or they can be created as extensions of commercial EHR software. Patients can examine information from the EHR in the PHR.

van Oudenhoven, B., et.al [5] The production process has become much more complex, and maintenance expenses have increased significantly as a result of modern industrial methods. Unlike Smith and Carayon-Sainfort, our model expressly positions behaviour as an outcome rather than a component of the work system. Performance is the result of conduct and in our model, it denotes the calibre of the maintenance choices that were made. Therefore, we stress that behavior comes before performance and investigate how PdM traits affect conduct as opposed to performance.

Braun, M., et.al [6] The process of gathering, organizing, and analyzing various data sets as well as creating the algorithms for artificial intelligence is the outcome of close collaboration between the research and the clinic, so this interaction between the two could be seen as a first essential prerequisite for the application of AI-DSS in the healthcare environment. When faced with vast volumes of data, AI-based apps can find and highlight relationships that academics and physicians might have missed otherwise.

Kumar, D. T. S. et.al [7] In general, there are two types of decision support systems: active models and passive models. In these models, the data is gathered and efficiently arranged, but no recommendations or decisions are made based on the information gathered. When using an active decision support system, data is gathered and processed to provide plans and solutions. Conversely, cooperative decision support gathers and analyses the information, and then refines the answers with human input to produce the most effective plans. Since gathering necessary information expedites Data-driven decision support systems, which facilitate better decision-making, first concentrate on the process of gathering data. Following collection, the data is altered to meet user demands. This is necessary since the data may be either organized or unorganized as a result of internal and external sources.

Zong, K., et.al [8] suggested the intelligent decision support system to promote long-term regional growth, which is based on big data. The system is appropriate for corporations and government agencies to use for advanced planning, cooperation, and administration. Modern transdisciplinary technologies like data mining, artificial intelligence for decision-making, and communications are included in this. The system makes use of a lot of data in many different formats, including text and multitasking, from a variety of sources, including governments, businesses, and nonprofits. A potential algorithm that could assist individuals in different roles in making judgement depending on the actions of others is the generalized Kuhn–Tucker bi-level programming technique.

Zuiev, P., et.al [9] The erosion potential approach, which hinges on the statistical analysis of many forms of data on the elements impacting the erosion process, is used to describe the time and space loss of soil erosion. The technique is distinguished by its high degree of dependability, simplicity that requires minimal computing power, and adaptability for usage in GIS. Regrettably, this method can only handle various cartographic data formats when a substantial amount of computer power is available. This method concentrates on making utilization of enough computer resources.

3. Methods and Materials

3.1 Mining Processes

Process models must be employed when configuring information systems that are aware of processes, like WfMS, ERP, and B2B applications [10]. The latter enables the data system to ensure and control proper operation of operational procedures by defining the sequence in which process steps are to be carried out.

Event logs are typically used to document significant events that take place in a PAIS. Process mining is the term for a group of a-posteriori analysis methods that make use of the data entered into these logs. According to various methodologies, events are often recorded in a sequential fashion where each event corresponds to an action (a clearly defined stage in the process) and is connected to a particular instance of the process. Additionally, there are other mining techniques that make use of additional data, like the performer or originator of the event—that is, the person or resource in charge of carrying out or initiating the action—the event's timestamp or data items associated with the occurrence. The issue that most "process owners" face—namely, their lack of knowledge about actual activities within their organizations—is tackled via process mining. In real-world settings, there is frequently a big discrepancy between what is expected or prescribed and what occurs. Process models can only be verified and finally utilized in an operational redesign endeavor with the support of a succinct assessment of organizational reality, which is precisely what process mining aims to provide.

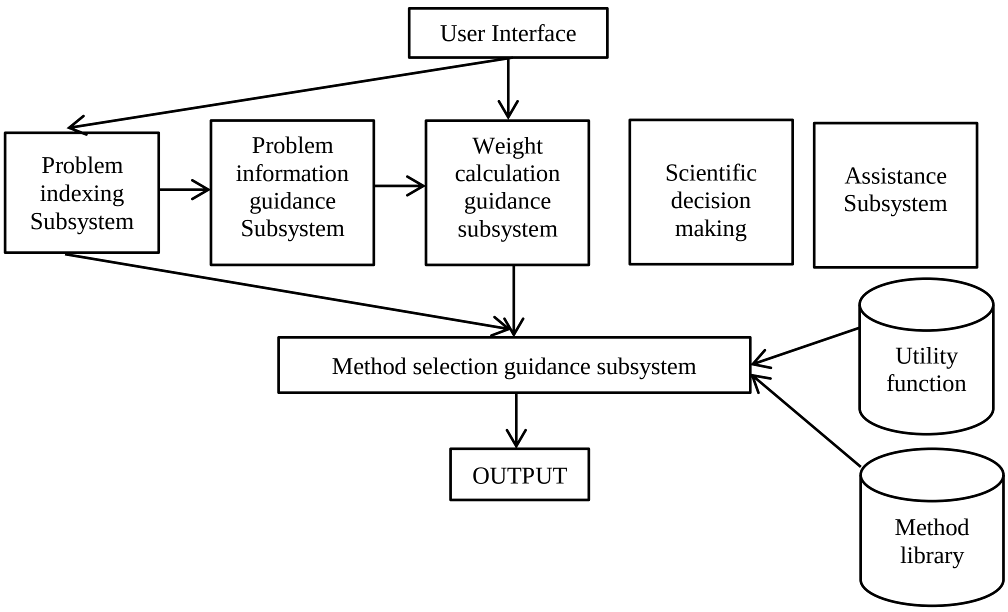

Fig. 3.1. Our suggested decision support system's structure

An unstructured or semi-structured computer application system that makes use of knowledge, models, and data to make decisions is known as a decision support system. In our study, we develop a decision-making system for human-computer interaction. Figure 3.1 depicts the framework of our approach. Process mining has often concentrated on process discovery, which is the process of obtaining details from enactment logs regarding the initial procedure model, the organizational context, and the execution attributes. The alpha algorithm is one method that addresses the control flow perspective. It can provide a Petri net model that explains the event log's behavior. Using the multi-phase mining technique, an Event-driven Process Chain (EPC) based on similar information can be constructed. The preliminary work on other model perspectives, such as organizational aspects, and data-driven business support systems, such as case handling structures, has now been finished.

The term "conform testing is an additional field of study within process mining. It measures and examines the differences between a process's model and its execution. One way to identify issues is with this. Lastly, enactment logs are not analyzed about the original model in log-based verification; instead, the log is examined for compliance with specific desired or undesired qualities, such as those stated in terms of LTL routines. It is therefore a great tool for verifying that a case complies with specific legal requirements or business policies. Currently, available tools include the ProM structure, which has a broad range of analytic techniques that may be used across the spectrum and applies to actual process laws.

3.1.1. AI Integration with the Process Mining Model

Based on matching a DSS, the proposed PM model's "proof of concept" with normal manufacturing processes, is explained in the schematic representation of Figure 3.2. New beginnings, semi-products, components that can generate energy, etc. are all processed by the manufacturing machine. The associated result, or output, is of high quality because of the automatic feedback control that incorporates AI judgment. The time machine's parameters can be changed or actions taken based on the values of the sensor data by the AI-supervised or unsupervised algorithms when anomalies are identified [12]. The BPMN notations contain a number of symbols, including pools, task containers, beginning and ending events, simultaneous and unique gateways, and, finally, exclusive event-based gateway modelling process checkpoints made possible by artificial intelligence techniques workflows for Konstanz Info Miner (KNIME) were used for the specific case studies are used to implement AI-supervised and unsupervised computations.

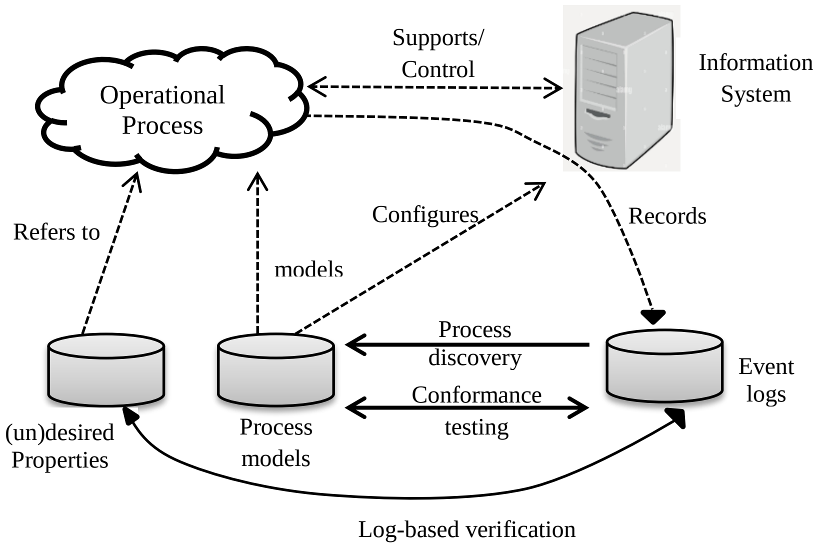

Fig. 3.2. Process Mining Model

3.1.2. DSS Primary Procedure

This pool, which incorporates the DSS to enable AI systems with supervision and without it, stands for the main process in the PM model. The algorithm selected is determined by the typology of available datasets. By using the "Exclusive Event-based" gateway, The choice is taken to process information using AI: if the monitored variables are checked positively, the manufacturing process proceeds; if the checks are negative, the AI algorithm can determine which intervention to perform or optimize the machine's parameter settings. A standard guideline setting or, depending on the warning level determined by the AI algorithms, a non-standard guideline setup (high alerting level requiring a significant adjustment of machine settings or further corrective action) will be initiated Predictive maintenance, potential production halts, significant control through the implementation of human resource operations, etc. are examples of corrective actions.

3.1.3. AI Engine (Control Model)

This pool relates to using the training and testing stages of the guided AI algorithm to process data. Predicted or categorized data defining warning risk maps that guide parameter adjustment and intervention strategies are the outputs. When a labeled variable—a major production variable that needs to be controlled—is found, monitored models are the most desirable. The subsequent pseudocode (Algorithm 1) explains the rationale underlying the data flow:

Algorithm 1: PM Pseudo code

1. *begin the production process;*
2. *initial production machine configuration;*
3. *Proceed with manufacturing (including parameter checking) until the conclusion of production if the machine's check is positive;*
4. *Select the appropriate optimal strategy using the Else (negative check);*
5. *If the unsupervised method returns a "True" result, then cluster your data and;*
6. *danger maps for structures;*
7. *If a moderate warning is predicted, the default machine should be used;*
8. *Limitation;*

9. If not, (high alert) implement additional corrective measures;
10. Close If;
11. Option (False) for the unsupervised algorithm in the supervised algorithm selection;
12. method that uses training to predict and classify data;
13. evaluating models;
14. If a moderate warning is predicted, the default machine should be used;
15. Limitations;
16. If not, (high alert) implement additional corrective measures;
17. Close If;
18. Close If;
19. Close If;

3.1.4. The Unsupervised Model of the AI Engine

The data clustering procedure this pool represents the definition of risk maps based on alert levels. The outcome is the data clusters that show the danger maps; when multiple variables need to be controlled without knowing the "weight" assigned to each one for a certain manufacturing process, unsupervised models are the recommended option.

3.2 PM Model Applications

The roasting process, which involves putting a food product through five ovens that are connected in sequence, is explained in the first instance of PV use. The plan uses a block diagram to show the product's journey through each oven, the input of the roasting process, and the packaging step, which streamlines the roasting process stream. A different set of sensors controls each oven. The temperature is the primary control parameter for the roasting process. First, the food product is inserted into the oven's input to complete the roasting process and then progressively placed into the remaining ovens.

Finally, the product is wrapped once it has been roasted. Controlling temperature or utilizing cutting-edge technology like Near-Infrared Spectroscopy (NIRS) are the usual methods used to verify the quality of the roasting process. An elementary method of assessing quality is to use temperature readings to confirm that each oven is heated evenly; it is recommended to use the clustering method to look at heat stability data clusters that contain values that are restricted to a certain area. In other words, it presents the conceptual PM model modified by the roasting procedure.

It is possible to verify thermal stability in every oven by allocating five "Exclusive Event-based" gateways in succession. If the thermometer readings are positive, the oven setting stays the same; if the temperature readings are negative, we run an AI unsupervised method called k-means clustering analysis, This produces a danger map with two levels of alarm. The risk map may show an average alert that allows the oven to be used at its default setting, a high alert that requires a greater setting (no usual parameter set), or both.

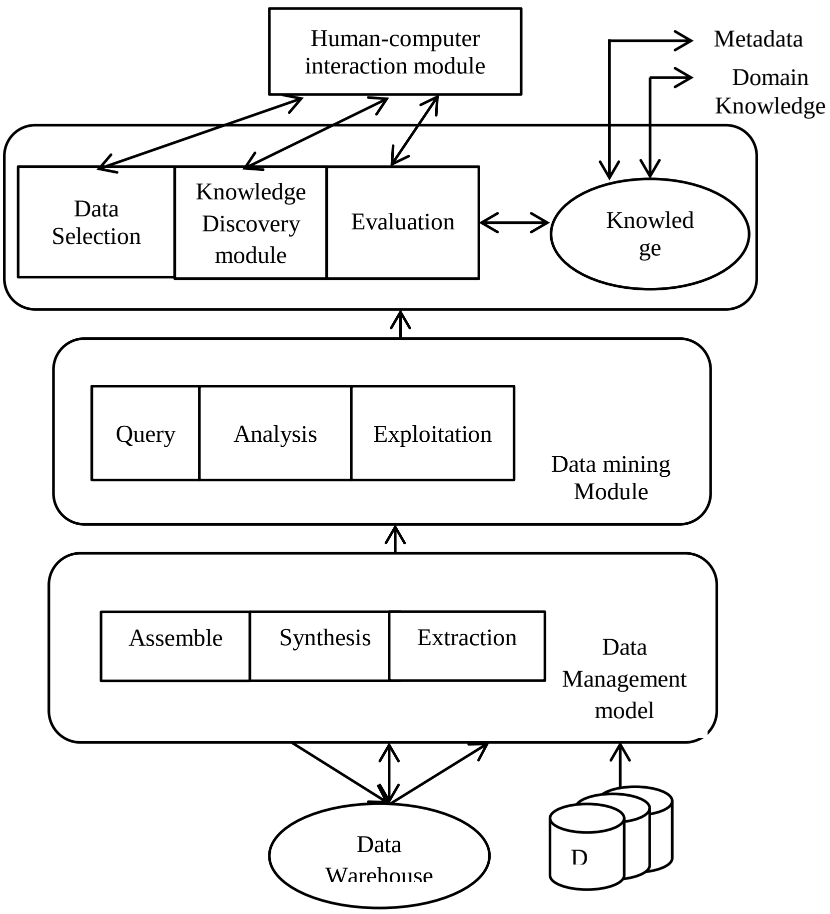

Fig. 3.3. The Decision Support System's Fundamental Architecture

Decision-makers have the option of making unstructured or semi-structured choices with the assistance of the intelligent decision-making system in Figure 3.3 [13]. Techniques from databases, models, methods, and knowledge bases are all combined. An intelligent decision support system is primarily composed of intelligent modules and a decision support system. Moreover, a crucial element of the decision support system is methodical human-computer interaction. To achieve this, system developers must not only research the overall programmer architecture, but also have a thorough understanding of the user's interaction style and computer skills to create the platform management interface, layout, and auxiliary control function that can adjust on its own and help users make better judgements.

4. Implementation and Experimental Results

This part contains a thorough experiment designed to confirm the efficacy of using data mining in the decision support system [14, 15]. Section 4.1 provides the evaluation of the data extraction, while Section 4.2 presents the parameter analysis.

4.1 Assessment of Data Mining

The performance of the suggested method is first assessed in this research using a variety of data mining algorithms, such as clustering, decision trees, Bayes networks, association rules, and concept lattices. The term "decision support system evaluation" describes how the user assesses the DSS, either favorably or unfavorably. In general, people can provide DSS with a brief, favorable rating if they like it. Users who dislike DSS can also give a poor assessment of the reasons behind their dislike. We compile user feedback on the decision support system to measure the accuracy rate of the system. The accuracy rate is defined as follows:

$$accuracy = \frac{Positive\ Evaluation}{Several\ Evaluation} \qquad (1)$$

The DSS's effectiveness is shown in Table 1 for various data mining algorithms. After ten iterations of the experiment, the mean is determined as the result. As Table 1 illustrates, the concept Lattice-based approach performs better. The concept lattice is a useful tool for decision support systems and can also be used to describe concepts at a high level. The issue of concept validity in reasoning with case systems following knowledge updates can be resolved by implementing a concept lattice in DSS.

Table 1. Shows the DSS's precision for several DM Methods

	DT	Bayes	AR	CL	Clustering
1	1.6284	1.7250	1.7893	1.8676	1.7327
2	1.6410	1.7392	1.7908	1.8762	1.7426
3	1.6513	1.7017	1.8093	1.8902	1.7897
4	1.6034	1.6993	1.8137	1.8365	1.6937
5	1.6197	1.7183	1.7900	1.8638	1.7213
6	1.5920	1.7427	1.7857	1.8365	1.7430
7	1.6211	1.7083	1.7902	1.8783	1.7104
8	1.6392	1.7200	1.8013	1.8607	1.7642
9	1.5907	1.7221	1.8109	1.8730	1.7553
10	1.6253	1.7173	1.7902	1.8635	1.7432
Ave.	1.6212	1.7194	1.7971	**1.8646**	1.7396

4.2 Analysis of parameters

In our study, there are two important parameters: α, which balances two terms in formula (2), and p, which indicates the fund's probability. We do trials with varying values of α and p. In Figure 4.1, the comparison outcome is displayed. As seen in Figure 4.2. The clustering approach performs best when the likelihood value p is set to 0.6. Performance is optimal for the concept lattice technique when ***U*** 핧 0.5.

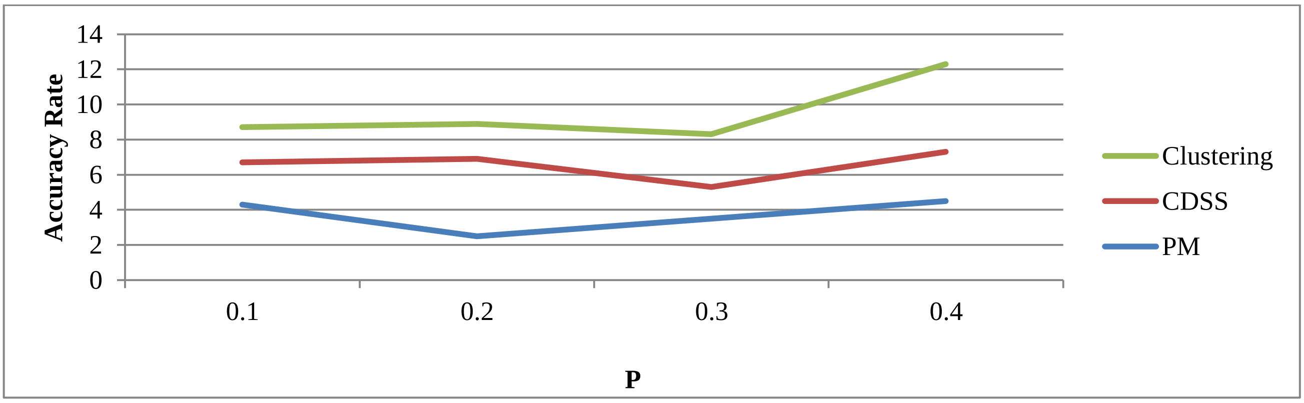

Fig. 4.1. The accuracy rate at various values of p

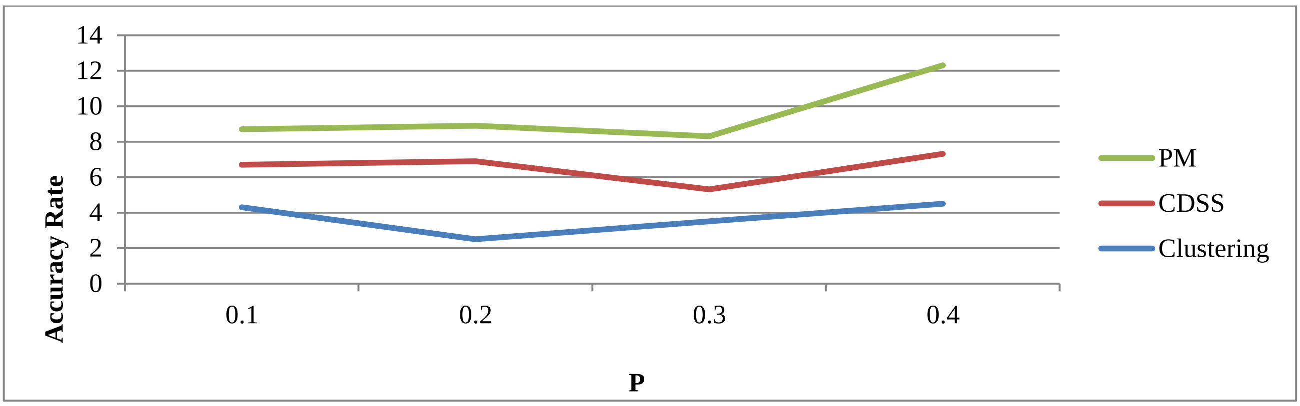

Fig. 4.2. Comparative outcomes with various parameters and accuracy rate with various values

The use of the PM model in automated production systems is one potential path for its development. In particular, AI tools can be integrated with production machinery through Human-Machine Interfaces (HMIs), enabling automated actuation control powered by the AI alerting output (by converting the output into an executable command driving machine via Programmable Logic Controller (PLC) protocols) [16. 17]. The examples that are described will assist readers in comprehending how the PM model may be used in various production scenarios. Because the theoretical model is adaptable, it can be used in a variety of situations that also involve significant adjustments to organisational and production models. Because the AI analysis triggers a sequence of corrective interventions based on the machine characteristics that are discovered, it has an impact on the organisational model of industries. In this case, the optimal production capacity for industries operating in various sectors can only be achieved through the deployment of CM models.

5. Conclusion

The suggested work offers a novel approach to process mapping that incorporates artificial intelligence into automated decision-making procedures. We go over a novel idea in which the PM model activates supervised and unsupervised AI algorithms, hence enhancing production processes. We have applied the BPMN technique to make the suggested model easier to compress. Two production instances are shown in our research to demonstrate how the theoretical model might be applied to a particular production scenario. Other relevant features of the PM method are also highlighted, such as the organizational impacts, the creation of risk maps based on production parameter prediction, the machine parameter-setting self-adapting processes, and potential integrations between PM and HMI. The first stage towards integrating cutting-edge Industry 5.0 processes into production systems is the PM model. All advanced electrical and mechatronic systems with checkpoint logic and automatic parameter settings can be designed using the PM technique.

An efficient and workable approach for the design of the decision support system is offered by data mining. Enterprise choices can be accurately predicted and analyzed using DSS which is based on data mining. In this work, we developed a visual decision-making system that benefits from the application of data mining techniques. We examined the data-mining-based decision support system's architecture. Additionally, a thorough experiment has demonstrated the efficacy of our suggested approach.

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