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Automating Daily Task in Manufacturing and Production Sites Via Machine Learning Intelligence

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Abstract: Robots have been utilized for some time now in the manufacturing industry. These robots work safely alongside humans and gain knowledge from their interactions with them. However, there are still sectors of the economy that are hesitant to adopt robots for a variety of reasons, including those pertaining to technology and the economy. The advancement of robotics has led to the creation of capabilities that span a greater breadth of applications than those that were previously utilized. In this paper, we develop an auto encoder based modelling to automate the daily task using robotic process automation in manufacturing and production sites. The unsupervised learning models achieves better processing of the automation and provides better accurate results than the existing methods. The software is able to perform simultaneous analysis on a number of logs, which enables it to discover processes and variations that were previously unknown. The platform has the potential to legitimately outperform technology-based businesses when it comes to the automation of processes, whether those processes are carried out in a physical or digital environment.

Keywords: *Task, Manufacturing, Production Sites, Machine Learning, Artificial Intelligence*.

1. Introduction

It is essential to adopt strong software engineering (SE) principles and techniques in order to construct machine learning (ML) software systems that are relevant in the real world. This is one of the goals of this project. Methods and approaches, which are supported by a wide variety of tools, are at the center of both the theoretical underpinnings and the practical applications of software engineering (SE). These were designed in order to guarantee the methodical design of dependable systems. During the development process of ML systems, other components that are not a part of ML models are taken into consideration [1].

In order for machine learning models to be trained, high-quality input data is required. After that, these models look for relevant patterns in the data, and based on the patterns they have learnt, they infer new knowledge about the world. When applied to ML models, the issues that surface as a direct result of employing erroneous information stand in stark contrast to the kinds of issues that are seen in conventional programming. Not only does this result in erroneous conclusions for that specific set of data, but it can also be used to support the building of a model that is incorrect or insufficient in general. Additionally, even if the model generates findings that are adequately accurate, its performance will substantially decline over the course of time regardless of how well it was originally designed.

Throughout the process of designing and maintaining software systems that are powered by machine learning [2, 3, 4], it is normal for there to be data inaccuracies, and it can be difficult to identify these flaws. Errors in data can result in considerable financial losses for organizations. To give you an example, LinkedIn experienced losses and was required to invest a large amount of work in order to expose data flaws in their job suggestion platform [5]. Error data can be caused by a number of factors, including a lack of knowledge of complicated data relationships, defects in application code, data drift from sensors, and data gaps induced by disruptions in network connections [6, 7, 8].

When doing an analysis to determine the quality of the data, it is imperative to take into consideration the data precision, completeness, consistency, and timeliness [9 - 13]. Data validation procedures really come into their own when working with extremely large amounts of data on a consistent basis. In order to assess the performance of

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machine learning (ML) software, a procedure that is conceptually analogous to this one is called the data validation method [14].

Even though there are a number of problems that can be discovered in the currently available data validation tools, such as flaws in the implementation and uncoupling from the data cleaning capabilities, a significant amount of emphasis is placed on the implementations of the various tools.

Despite the fact that these tools are currently under development, this remains the case. Documentation regarding adoption experiences with the data validation procedure is produced exceptionally infrequently. The members of your team who are just starting to put ML-enabled software solutions into production could stand to benefit greatly from the lessons that are taught in this article. Engineering demands a significant time and financial investment in order to develop and maintain a validation [15].

Developing and maintaining a data validation method and instrument since established protocols does not exist for building a validation process, there is no way to guarantee that the overall quality of the data will be high. The vast majority of engineering teams choose not to incorporate data validation tools into their processes if those tools do not fulfill particular requirements [16]. The primary reason for this is the difficulties that is involved in carrying out the task. This would be a concern, for instance, if it caused workflows to produce obsolete data as a result of higher wait times [17].

It is now appropriate for use in modern services in addition to taking on responsibilities that are significantly more complicated. Peripheral components of a system are more amenable to the incorporation of new technology than central components. During the current iteration of the collaborative assembly process, the modules responsible for power, protection, and interface have all been described. During this process, humans and robots will collaborate in close proximity to one another in an open setting.

2. Related Works

With the support of the strategic framework that automation provides, many automation technologies can be adopted independently of one another. In order to accomplish this goal, it is necessary to locate tasks, possess the flexibility necessary to reuse automated operations, and make the most of the capabilities offered by the automated system [18]. The goal of automating a process is to make it more effective while also reducing costs. This can be accomplished through the implementation of a number of different strategies, including the standardization of routine tasks and the enhancement of the utilization of data received digitally. This can be accomplished by reducing the amount of time that is wasted and making more efficient use of the data that has been acquired [19].

These data can assist organizations in making decisions that are both more informed and more timely. Businesses can, among other things, grow, become more integrated, and operate more efficiently as a result of automation capabilities [20]. Our comprehension of the potentials and confines offered by RPA technologies has been expanded, and clear answers to the issues raised by these technologies have been supplied. separation from frameworks whose sole purpose is to concentrate on the production of automation tools or concepts. The following is a review of the many key capabilities of automation that can be used to improve automation in industries. This topic is shown in Table 1.

Table 1. Capabilities of Task Automation in Buildings

S. No	Capabilities
1	Automate business
2	Increase human skill
3	Scalability of operations
4	Gain flexibility
5	Improve operational efficiency
6	Detect risk
7	Efficiently functioning
8	Automate repeat operation
9	Speed the digital process

10	Automated Billing
11	Automated workload

If organizations are going to be able to fully automate their processes, the technology of today has to be able to overcome the limitations imposed by older approaches. Companies now have the ability to expand beyond the limitations of certain processes and find the most effective methods for automating a wide variety of high-level, high-volume jobs. This is made possible by advances in information technology. Automation provides businesses with advanced analytical tools to assist such businesses in overcoming the limitations of relying solely on a single data collecting platform [21].

Instead of adding artificial intelligence, it enables business customers to automate the entire process of jobs at once. This is a significant time saver. For the automation process to be successful, it is essential that the existing information technology infrastructure and business processes of the company continue to function normally. The gap that previously existed between traditional computer systems and automation has been bridged by a technology known as robotic process automation. In order to accomplish this goal, it makes use of a vast array of machine learning, pre-packaged software, and labor automation technologies [22].

The only way for the lives of workers to get better is for their company to become more successful and have higher levels of production. Automation in the manufacturing business is made possible by employing a wide range of digital technology in a variety of different applications. Even if automation has been utilized extensively for a considerable amount of time, it is currently of the utmost significance to adapt to the nature of automated systems, which is constantly evolving. Despite the fact that automation has been widely utilized for a considerable amount of time, this remains the case [23].

3. Proposed Method

The application of machine learning can result in improvements that are optimized not just in terms of efficiency but also in terms of quality as illustrated in figure 1.

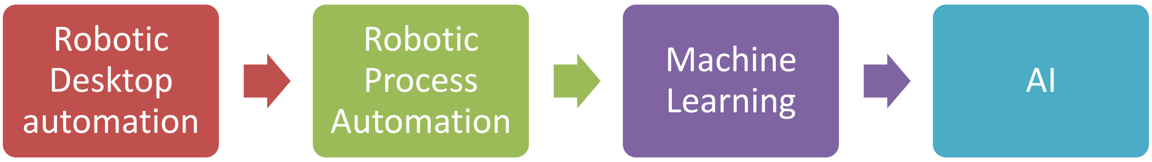

Fig 1: Process of Automation

Fig 2: Role of Manual and user intervention in Automation

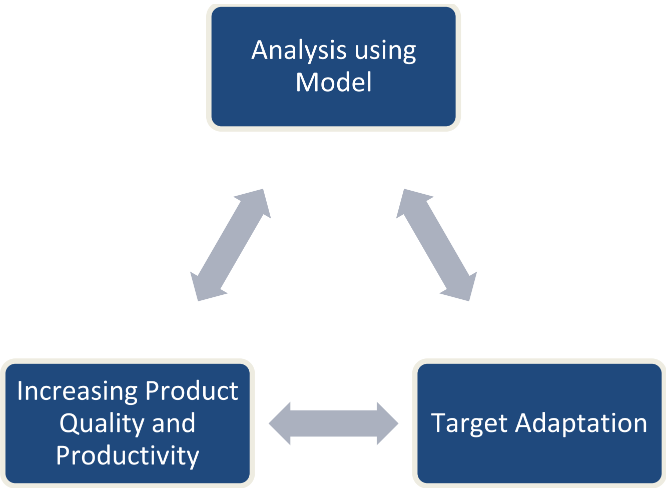

Fig 3: Proposed Modelling

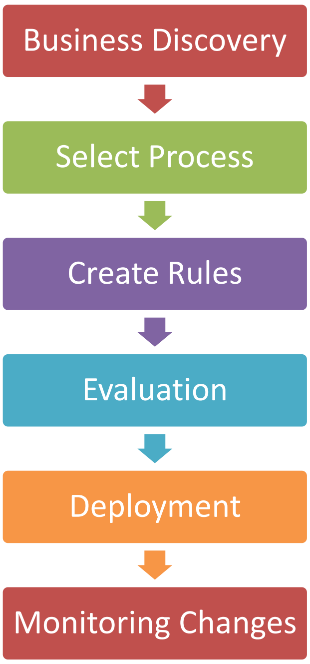

Fig 4a: Process of Automation

The ability of RPA, to process unstructured data inputs by capitalizing on powerful AI capabilities considerably increases the automation and broadens the scope of its potential applications. The RPA lifecycle provides a structure for the automation process, acting as a framework that enables quality control at each stage of the lifecycle. The usual manner of carrying out the implementation process is illustrated in figure 2, which can be found here. As can be seen in Figure 3a and b of the implementation pipeline for cognitive robotic process automation, the cognitive capabilities of the system to learn and make decisions. This is an important step in the development of cognitive RPA.

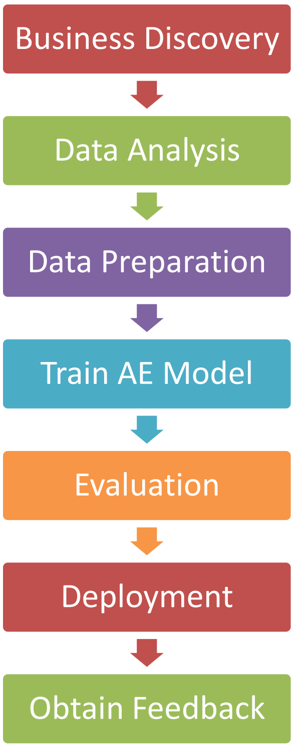

Fig 4b: Proposed Process of Automation with AE

Auto-encoders, also known as AEs, are a well-known unsupervised learning method that may be applied to the process of instructing neural networks how to learn representations. AEs are abbreviated as AE. Auto-encoders are typically applied when working with data that has a high number of dimensions, and dimensionality reduction provides an explanation for how the data in question is represented. Both of these processes are referred to as dimensionality reduction.

Autoencoders are constructed with an encoder, a code, and a decoder all incorporated into its design. The input is compressed, and the encoder produces a code; the component that is responsible for decoding the code is called the decoder. In recent years, generative data models have been taught with the assistance of artificial engineers.

Autoencoders are networks that strive to encode input into a latent space and decode it subsequently. This is how they got their name. Unsupervised learning is a form of learning that permits the extraction of generally beneficial attributes from data that has not been labeled, and its name comes from the fact that this method of learning is unsupervised.

Figure 4 depicts the architecture of an autoencoder. As can be seen in the figure, the architecture of an autoencoder consists of both an encoder and a decoder. After being processed by the encoder, the data are then output as low-dimensional latent vectors. The encoding process begins with the data being fed into the device. The data from the output stream are sent via the decoder, which makes use of those latent vectors in order to recreate the data from the input stream. Data compression, denoising, and anomaly detection are just a few examples of significant applications.

Fig 5: Auto Encoder Process

The operation of an autoencoder starts with the compression of the input data into latent vectors (which are not displayed), as shown in Figure 5, and is then followed by the re-decoding of the vectors into the starting data. This may be seen in action in the figure.

An autoencoder that is built up of convolutional layers, also known as a Conv autoencoder, is utilized in place of a traditional autoencoder such as a fully connected autoencoder since the Conv autoencoder is superior at managing the data associated with 2D images. In case you were wondering what a convolutional autoencoder looks like, this is an example of one. Evolvable filters are used to construct the layers of parameters that make up convolutional neural networks (CNNs), which are becoming increasingly popular for their application in the interpretation of visual input.

CNNs couldn't function without the indispensable conv. An activation function, such as the rectified linear unit (ReLU) or the sigmoid function, is responsible for the generation of a two-dimensional feature map after the input data has been processed by the Conv. In addition, the resistance that exists between the filter and the data that is being input is computed by making use of the data that is being input.

$$aout=max(an\times ninu(n,n)) \quad (1)$$

The spatial continuity of the feature map must be preserved in order for the pooling layer to fulfill its primary function, which is to concurrently reduce the resolution of the map. This results in learning that is both more quick and more compact, while also minimizing the amount of processing overhead. When the window function u(x,y) to the input $a_n x n_{in}$, is applied using max pooling that minimizes the size of the input by substituting each neighborhood with the maximum value aout. This results in a smaller amount of input data. This results in a reduction in the size of the input.

For a variety of different causes, one begins to suffer degradation problems when deeper networks begin to converge. This difficulty becomes more severe as the network depth increases, which ultimately leads to a drop in accuracy. It is difficult for autoencoders to gain an understanding of the circumstance based on the data when they are presented with this obstacle. As can be seen in Figure 5, in order to remedy this problem, we put in place skip links between the encoder and decoder levels. Because of the skip connections that are present between the encoders and decoders of each layer, it is possible for the issue of pixel-wise prediction to converge to a solution that is more optimal. X1 will be used to represent the outputs of the encoder layer, and X2 will be used to represent the outputs of the decoder layer. As the input to the succeeding decoder layer, you should make use of the formula that is listed below:

$$F(X1,X2)=X1\oplus X2 \quad (2)$$

The network makes use of skip connections so that the various components of the feature maps that are utilized by the encoder and the decoder can be combined together. These maps are used by both the encoder and the decoder. This facilitates the process of recovering the picture in some way. During the course of this research, an autoencoder was utilized and instructed to learn how to reconstruct normal images from ones that had been tampered with.

The table encoder and decoder portions make up the upper and lower tiers, which are situated above and below the table central horizontal line, respectively. The part of the system known as the encoder is responsible for converting encoder data, which has a size of 400x400x3, into latent vectors. In the meantime, the component known as the decoder is responsible for producing decoder data, which is also of size 400x400x3 in its entirety. This encoder makes it feasible for the defect image to be reconstructed as a defect-free image during the decoding process so that it can be displayed correctly. After that, the image that was generated can be utilized during the process of defect detection image subtraction.

Both batch normalizing and the ReLU activation function are utilized in each and every convolutional layer that is present. The first step is to do batch normalization. Models are able to rapidly assimilate new information thanks to the ReLU activation function, which enables them to learn properties from data that are significant both quantitatively and qualitatively. Each skip connection combines the conversion output from the encoder with the upsampling output in order to make up for any data that may have been lost as a result of the compression process that took place in the encoder. This is done in order to compensate for any data that may have been lost as a result of the compression process.

It is possible to disassemble the autoencoding process into its component parts, which are as follows:

(a) *Encoder*

Encoder, a function for the extraction of features that generates a feature vector based on the inputs that are provided; this function is part of the feature extraction process. Since this is the case, we may define the encoding datasets as $x(t)$ and the encoder function as f_θ, which will give us the following equation (3):

$$h(t)=f\theta(x(t)),x(t)=\{x(1),\ldots,x(T)\} \quad (3)$$

where h(t) - features vector.

(b) *Decoder*

Using Eq. (2) as a guide, decode a function g_θ that transforms the input space into the feature space. This function transforms the input space into the feature space.

$$r=g\theta(h) \quad (4)$$

Probabilistic models are constructed and trained on the basis of a probability function that has been provided in order to maximize (roughly) data similarity. The data are compared to the function in order to accomplish this. The process of teaching autoencoders to decode data can take place in a variety of different ways. Both the encoder and the decoder have had their respective parameter sets trained so that they can produce the same primary input. This guarantees that the product they create will be the same. In the process of reconstruction, every effort is made to leave as little room for error as is humanly possible. Applying the equation results in the determination of the reconstruction error, which is denoted by the symbol $L(x,r)$. It provides a numerical value for the difference between the original version of x and the reconstructed version of x, which is denoted by r.

$$L(x,r)=\|x-r\|^2 \quad (5)$$

Training an autoencoder can be summed up in a few words as the process of locating the parameter vector θ that results in the least amount of reconstruction error is applied, where $x(t)$ represents a training example. This can be said to be the process of minimizing the amount of error that occurs during reconstruction.

$$JAE(\theta)=\sum L(x(t),g\theta(f\theta(x(t)))) \quad (6)$$

To accomplish the goal of lowering the value in question, the stochastic gradient descent method is utilized the vast majority of the time. This method is conceptually comparable to the multilayer perceptron training approach.

4. Results and Discussions

For the experiments, the following of hardware are utilized, which is shown in Table 1. Before the NN can be trained, there must first exist a dataset that it can draw information from. To the best of our knowledge, there is no dataset that is open to the public that is concentrated solely on user interfaces. We were able to confirm this by looking into the matter.

Table 1: Hardware Specification

S.No	Specification
1	4 Terabyte Storage in build Capacity
2	Intel i5
3	NVIDIA Graphics Card
4	8 Terabyte Memory

Therefore, the researchers who were responsible for this study are the ones who should be held accountable for the creation of the dataset that was used in their work. The dataset can be broken down into three distinct subcategories: training, validation, and testing. Each of these subcategories can be extracted independently.

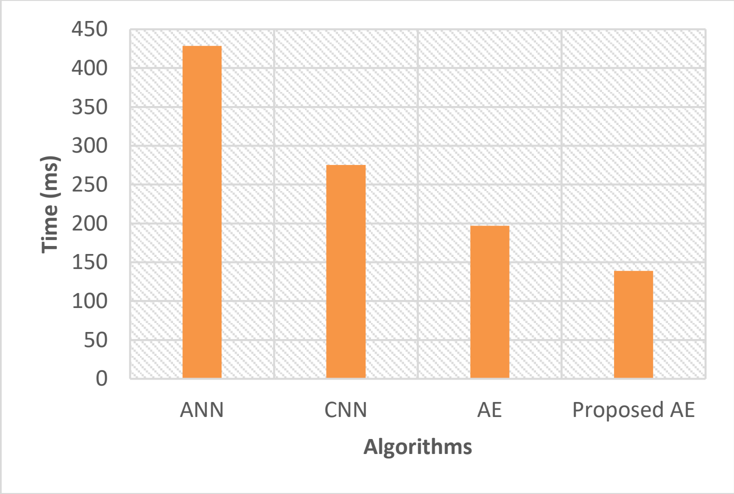

Fig 6: Training time

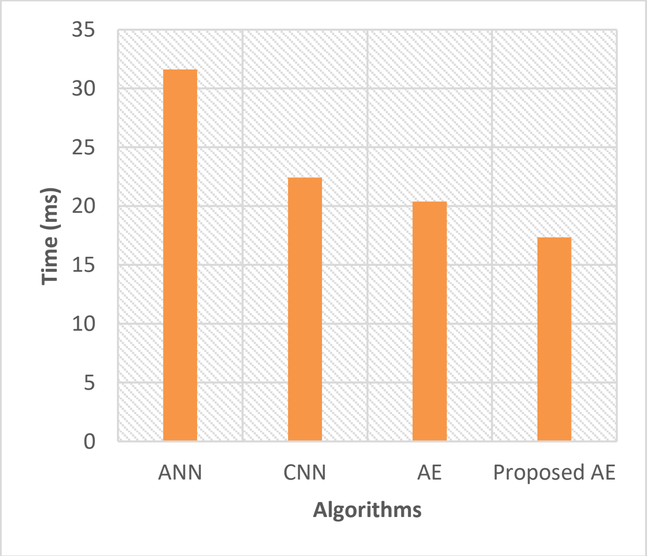

Fig 7: Testing time

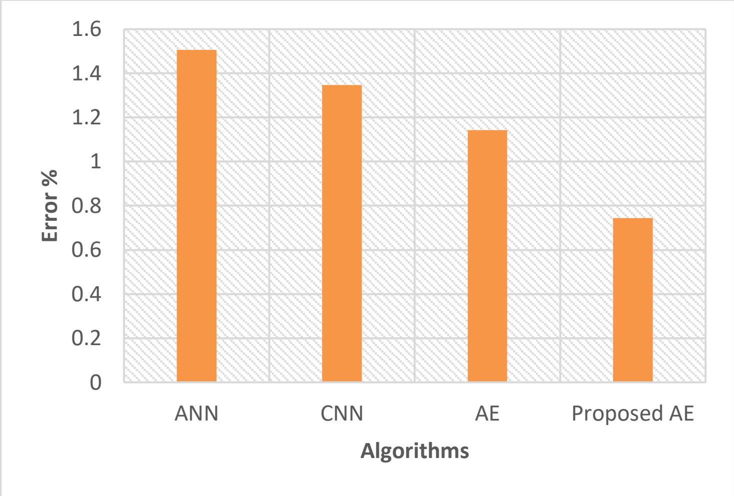

Fig 8: Training – MAE

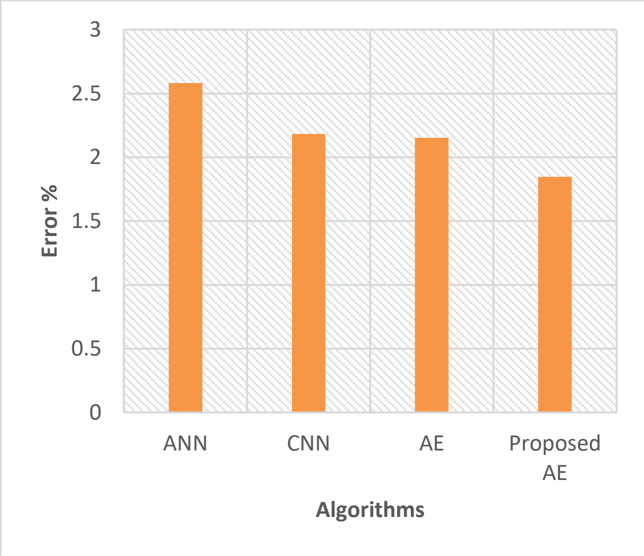

Fig 9: Testing - MAE

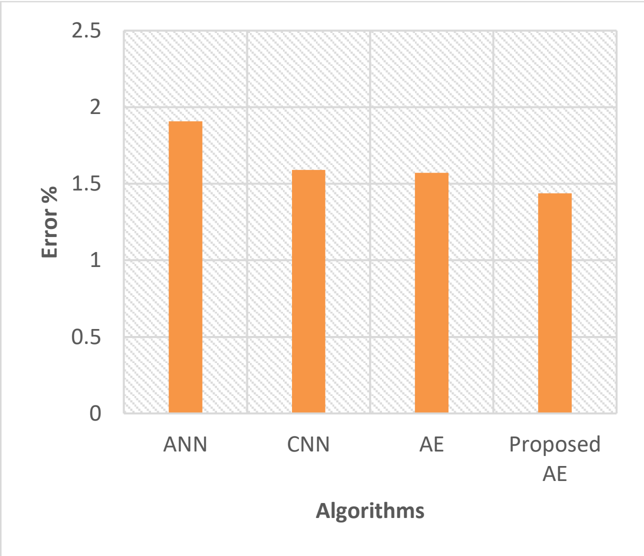

Fig 10: Training – RMSE

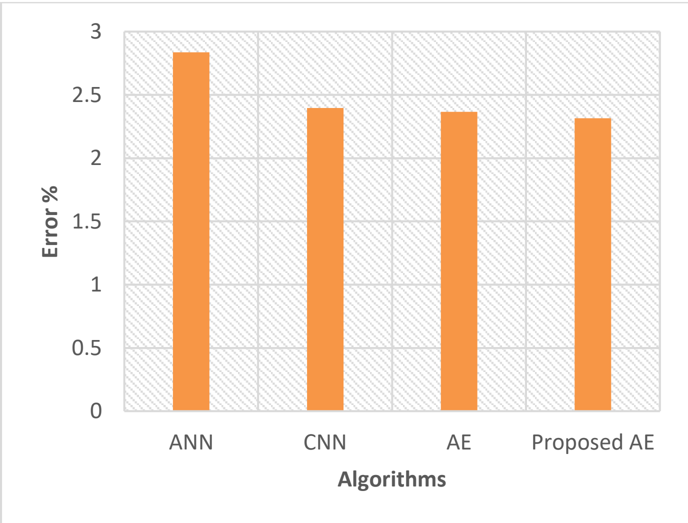

Fig 11: Testing - RMSE

If companies want to keep up with their current level of success in the market, their products will require an increase in overall quality. In the event that certain quality standards are not met, either the production line will be brought to a end, or the finished product will fall short of the requirements set forth by the customer. The concept of consistent takes on a different connotation depending on the kind of product that is being discussed.

This concept of consistency can be extended to cover the entirety of the manufacturing process by including production factors such as the quantity of raw materials used, the amount of time it takes to manufacture the component, and the number of people who are needed to finish it. This would bring the concept of consistency in line with industry standards. When one is attempting to maximize a certain set of output factors, it can be difficult to learn everything about a manufacturing process that is necessary to do so in order to achieve that goal. Existing systems are already optimized for the precise execution of establishing criteria; however, self-optimizing systems should be used in order to achieve the highest possible level of output consistency.

It is necessary to have professional knowledge of the mechanisms and boundary conditions that execute each phase of the manufacturing chain in order to have a complete understanding of this concept. Only then will you be able to comprehend it in its entirety. They consider it to be standard practice to modify already-existing content in order to incorporate newly developed features, and they see it as perfectly acceptable to do so. Every new generation of manufacturing machinery and control technologies brings with it improvements in both the effectiveness and dependability of production systems. This trend is expected to continue. The manufacturers use materials that are more resilient and incorporate quicker actuators wherever it is feasible to do so. It is possible to achieve better control of the circuit and permit faster coordination with the unit through the implementation of faster bus systems that are equipped with sensors. This makes it possible to achieve both of these goals.

In particular, the results of our tests indicate that statistical learning in latent spaces leads to fewer errors on average and can achieve satisfactory performance with a reduced number of data points. Additionally, our findings suggest that this type of learning can be accomplished with a smaller number of data points. It is a well-known fact that the process of reinforcement learning in latent spaces is both noticeably quicker and more reliable than in other settings. In each and every experiment that we carried out, we found that learning in the AE-based latent space performed noticeably better than the methods that are currently considered to be state-of-the-art. In comparison to DAE, the results obtained are consistent with the idea that deep autoencoder neural networks have superior performance in terms of approximation.

5. Conclusions

The purpose of automation is to enhance sustainability while simultaneously increasing savings and generating additional income. The achievement of this objective is made possible through the integration of automated technology and instruments with human labor. Businesses have the opportunity to educate themselves on the various methods of automation, how these methods relate to one another, and how these methods can be aggregated and facilitated in order to acquire the appropriate tools and put them to use in their operations. It is necessary for software to be able to communicate with one another as the use of automated processes becomes more widespread. In addition, the development of new tools that enable plug-and-play architectures could be of assistance to businesses in their efforts to successfully scale up their operations. The term automation refers to the process of fully automating a process by putting in place a toolchain. When using this approach, companies are able to automate not just a portion of their business processes but rather all of those processes altogether.

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