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A Systematic Literature Review of Failure Prediction in Production Environment Using Machine Learning Technique

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***Abstract*—Context: Process continuity is one of the fundamental quality attributes of a production environment. The accurate prediction of a process failure is a significant challenge for the effective management of the production delivery process.**

Objective: The primary aim of this paper is to present a systematic review of studies related to the prediction of failure in production environments using machine learning techniques. Several research questions were identified and investigated in this review, with the goal of providing a comprehensive summary and analyses, and discussing various viewpoints concerning failure prediction measurements, datasets, metrics, measures of evaluation, individual models, and ensemble models.

Method: The study employed the usual systematic literature review methodology and was limited to the most widely used digital database libraries for computer science from January 2016 to May 2021.

Results: We examined 42 relevant research published in peer-reviewed journals and conference proceedings. The findings indicate that there is just a small amount of activity in the region of the production environment using failure prediction compared with other service quality attributes. SVM, RF, DT, LR, and LSTM were the most used ML techniques employed in the selected primary studies, and the most accurate is the prediction model using ANN. Most studies concentrated on regression problems and used supervised kinds of machine learning. Individual and ensemble prediction models were used in most investigations, with the number of studies using each type being nearly equal.

Conclusion: According to the findings of this comprehensive literature analysis, ensemble models outperformed individual models in terms of accuracy prediction and have been found to be helpful models in predicting faults or unexpected events. However, their use is rather infrequent, and there is a pressing need to put these and other models to use in the real world to a large number of datasets with a diverse collection of datasets in order to improve the accuracy and consistency of the findings.

***Keywords*—Failure prediction, machine learning, production, predictive analytics, deep learning**

1.0 INTRODUCTION

Experts are referring to the Fourth Industrial Revolution as "Industry 4.0." This is heavily connected to how integrated the production and operational environments are. Information concerning procedures, events, and alerts that occur while an industrial production line moves down the line is compiled into a large volume of data, as measured by industrial systems. When this data is processed and examined, it can provide important information and knowledge. Through the use of analytic methodologies that utilize data, it is feasible to obtain interpretive findings for strategic decision-making, offering advantages such as decreased maintenance costs, fault reduction, and extended life cycles of products. In this paper, we studied previous papers regarding predicting failure using the Machine Learning (ML) technique in a production environment.

A failure, by definition, is misbehavior that diverges from the intended service and is unable to deliver it [1]. In this article, the intended service is a machine learning technique. The word "Prediction" is similar to "forecasting," and the combination of "Failure Prediction" here means to forecast or predict the misbehavior of incidents in a production environment. In the full context of the definition, it means forecasting the misbehavior of incidents in a production environment using the ML technique.

Predictive models are mostly based on classifications, and regression is reported to be the most widely used technique [2]. In the [3] classification scheme, each object is identified by one of the predefined classes or groups. For example, in an operating system context, a new class "fail" can be created and called "non-fail", in which crashes are placed according to variables described in the classification. Regression has the dual purpose of helping us recognize the association between various variables, while innovation does not. In a large-scale OS infrastructure, unreachable data is most important, and intermittent data serves as a check on the overall system efficiency, while statistical data regression is used to help discover the relationship between the variables. As per [4], regression is used with continuous variables, and categorical variables are handled using supervised learning. Neural networks, decision trees, and support vector machines are used in an infrastructure to identify, distinguish, and triage issues.

In this analysis, prior works of literature were examined to classify their common machine learning approaches, while a number of machine learning techniques, their errors, and their relative levels of success are discussed in this analysis. A dependable model for anticipating and limiting infrastructure failures is critical to success. Artificial intelligence has made Machine Learning (ML) a particularly important resource for constructing intelligent predictive algorithms in numerous fields. ML techniques have the capacity to handle complicated and dynamic situations, such as those seen in the industry, and to find concealed correlations within data using several dimensions and multivariate data [5]. Therefore, the application of ML in a production environment enables powerful prediction approaches. However, it is also dependent on the correct selection of an ML algorithm. In order to accomplish this goal, the paper offers a Systematic Literature Review (SLR) featuring the most up-to-date methodologies in the prediction market using ML methodologies. This paper provides a great starting point for anyone who is interested in ML and its primary results, as well as for anyone working in a production environment. That means our SLR is innovative, and we look forward to AI scholars and practitioners making a significant contribution to this field. This paper's greatest contributions are as follows.

This research is a study of the work done in the AI field using ML for prediction. The author conducted a comprehensive study that involved 40 relevant pieces of research, all of which were compared to discoverable questions. In order to estimate potential gaps, it must be first identified as a potential research possibility in predicting a failure.

This study follows the structure illustrated in Section 2, which introduces the research approach utilized to complete this literature review. Section 3 summarizes the SLR results and deals with our primary focus questions for research (RQs). Section 4 wraps up this study by identifying its shortfalls and shortcomings as well as identifying important research needs.

2.0 METHODOLOGY

The review analysis here will attempt to find, define, describe, and explain all existing ML models. This SLR takes subsequent learning and advice from [5] into account. Typically, three distinct phases are identified: planning, executing, and reporting. Eliminating the likelihood of researcher bias in the form of an acceptable protocol during the planning stage consists of these steps: first, establishing an achievable objective; then devising a way to achieve it, which was outlined in the introduction; and, finally, implementing the procedure. This is a critical component of doing a critical evaluation. During this phase, authors formulate RQs to focus on the main points, the process, select studies based on the quality assessment, and document the findings [6]. At the end of the process, all analysis would lead to the final discussion and reporting, with just one phase separating them: sharing the findings and the answers to each question.

2.1 Sources

To build this SLR, the author adapted the review protocol from ROSES (Reporting Standard for Systematic Evidence Syntheses). This protocol is suitable to be adopted as it is comprehensive and arranged [6]. Besides, [7] also emphasized that this protocol will help a lot with the flexibility of the methodology and can be applied whether it is a quantitative or qualitative research type. By using this protocol, this SLR starts with the research questions' development, systematic finding strategies, and data extraction and analysis.

2.2 Research Questions

Questions had been defined to seek probable resolutions to the objectives. Below are the questions in this study:

Q1. What are the ML methods that are being used to perform failure prediction in production?

Q2. What is the accuracy level, and which is the best technique for applying ML in failure prediction?

Q3. What type of industry adapts the failure prediction model using the ML technique?

Q4. What is the subject of failure employed in the failure prediction model in production?

2.3 Systematic Finding Strategies

In this subtopic, there are three major parts involved in the process of paper selection, which are identification, screening, and eligibility. These will be explained further in the following subtopics.

2.3.1 Identification

To begin the list of search strings, synonyms and alternative terms have been combined with the Boolean operator (AND, which has the effect of narrowing and restricting the search, while OR helps to extend and widen the search) and the truncation symbol (∗). In this SLR, the following search terms were created: ("failure prediction") OR ("fault prediction") OR

("failure forecast*") OR ("predictive failure") OR ("predictive analytics")) AND (("machine learning") OR ("machine learning technique")) AND (("production") OR ("production environment")). Looking at the keyword search, it can be divided into three parts by the AND operator. The OR operator is used to find the synonym of the word.

2.3.2 Screening

In the initial search, both the selected databases and the full-text documents, including conference proceedings, were searched using the words selected in the search bar. Thousands of unrelated studies were returned, so the search results were restricted to journal article papers only, based on their titles and abstract contents. It was discovered that some duplicate papers were present in these databases, and the duplicate papers were subsequently deleted. Additional studies were found by referring to the citations of the studies that had been described as important by other researchers. After we had retrieved the primary studies from the primary search, we scanned the titles and abstracts to identify specific studies. A bit of additional research was done to uncover which relevant studies could be found by reading the results and discussions.

2.3.3 Eligibility

Eligibility screening was performed to make sure all the selected papers were valid and could be included in this position paper. By referring to the article title and summary, the procedure was completed. The methodology, findings, and discussion parts of the report were cited whether the study results or results of either article were selected appropriately or not after reading the title and abstract of the study. Since the emphasis was not on failure prediction in the production environment, duplicated records, studies that were conducted not using ML techniques, and scoping review articles, resulted in 225 papers that were published. After running the first phase, 44 papers were chosen to undergo the next step.

2.4 Quality Assessment

This relates to mixed methods assessment tools known as MMAT (Mixed Method Appraisal Tools), as SLR includes papers or references from various research designs (quantitative, qualitative, and mixed methods) [8]. Articles were assessed based on two factors that fall under the general umbrella of quality and a number of criteria related to the study design of the paper. Next, we conducted an assessment of the article content by assessing two primary variables, namely ‘Are the study questions clearly formulated?’ and ‘Does the data contained in this study address the research questions mentioned above?’. To move on to the next step, the article must first pass through all the stages before the design of qualitative or quantitative analysis or mixed methods is decided and subsequently evaluated based on five criteria. Three response options were provided: Yes or No, and if they were uncertain or unable to discern the results, they chose Not Sure. Each evaluator conducted the evaluations alone. If no agreement is reached, a second opinion was sought. Only quality papers that meet all five requirements were selected for inclusion in the SLR. A total of 44 papers were analyzed, and 28 met all three criteria, while the other 22 failed to meet any one of the specified minimum requirements.

2.5 Data Extraction and Analysis

If the papers have been shown to be of good quality, the next step is to extract the data from them. Two researchers carried out this operation. The information extracted concentrated on the key sections of the study; the abstract, the results, and the discussion. Other related data from the article were also included in the readings.

Data extraction is the first step, and the subsequent step is data analysis. For this SLR, which integrated a mixed method research design that incorporated qualitative mixed methods as well as quantitative methods, it is preferable to perform a qualitative synthesis [9]. Quantitative analysis, as used in qualitative synthesis, is one of the best methodologies for form analysis, according to [10]. Theme analysis is a form of research analysis that analyzes previous studies to identify recurring patterns and related findings.

The findings were analyzed one by one in order to find a fitting theme. If similar or related findings were found, they were compiled into one data set. Following the previous theme, the group would then be given a new one. There are four primary themes in this process: 1) techniques related to ML; 2) industry; 3) failure prediction; and 4) accuracy. When this research was repeated for the sub-theme creation process, the results in each of these themes were analyzed again for potential sub-theme formation, and this process resulted in only major themes that had been decided to be captured. Subsequently, all these themes were evaluated all over again using this method; all four major themes were kept while only a few of the original themes remained. Two of them were eliminated. In the end, the two experts in the field of SLR and information technology, one from each field, evaluated and concluded that all four key themes were formulated correctly, applicable, and acceptable to the study's query.

This paper considered the following planning protocol for the review:

• Exclusion criteria

E1. Works not related to production and ML.

E2. Works that do not present any type of experimentation or comparison results and makes only propositions.

E3. Works dated before the year 2016.

• Quality criterion.

QC1. Papers that compare the accuracy results using different ML techniques.

3.0 RESULTS AND DISCUSSION

Following from the data obtained from primary sources, this section presents information on the search, a visualization of years of publication, and citations.

3.1 Selected Primary Studies

In this SLR, 44 primary studies were selected to compare and evaluate the studies in the software maintainability prediction domain and are summarized in Fig. 2-1. The following Figures 2-2, 2-3 and 2-4 provide an overview of each selected study and contain the following attributes: study numbers been made, number of citations, and the publication year.

• Data extraction fields

D1. Employed ML method, being able to consider any classical ML technique of the state-of-the-art or new ML techniques.

D2. The system that has been applied to the failure prediction strategy being either solely failure detection or only prevention to any specific preference.

D3. Data samples that have been used for ML purposes and the desired (output) predictions.

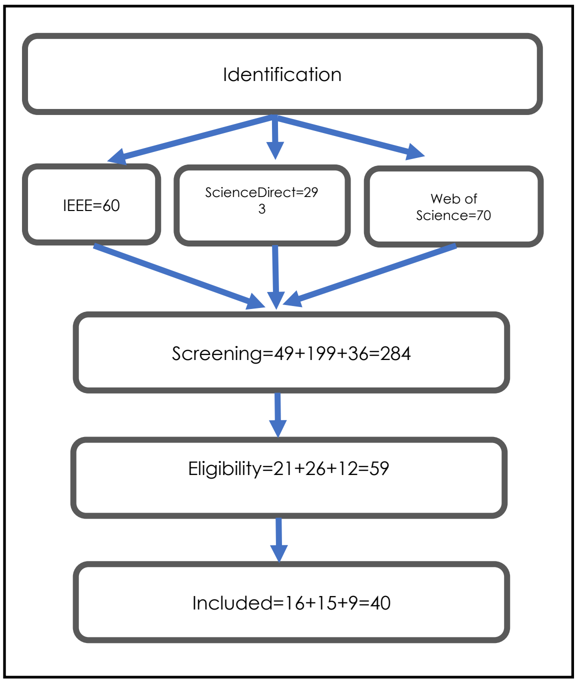

Fig. 2-1. Flow diagram of adopted PRISMA

Based on the PRISMA adoption figure in Fig. 2-1, a total number of 423 journal articles were retrieved during the identification process. This is known as first level selection and the number of articles gave a general or rough selection according to the keywords inserted. Secondly, there is a screening step to the identification output of articles to check on the unnecessary elements based on the abstract, methods and conclusion. The screening process also removed the duplication of articles and resulted in a total of 284 articles that were included in the eligibility process. An eligibility step responsible to check on full-text accessibility produced an output of 59 articles. Lastly, the included process that concluded the PRISMA step resulted in 42 articles.

3.2 Publication Years

The publication years of the selected primary studies were between the years 2016 and 2021, and the figure below shows the number of studies published during those years. Moreover, there is an indication of increased publications after 2018, and the researchers started to make more use of industry or real-world production datasets. The number of publications from the beginning of 2021 up to when this study was conducted has passed the volume published in 2016, 2017, and 2018. It is expected to increase exponentially before 2021 ends. The significant increment in 2019 and 2020 shows the usage of applications of ML in propositions with IR4.0 and artificial intelligence. ML applications such as in cloud providing useful information to users, for example analyzing big data to filter variables, make ML articles crucial to developers.

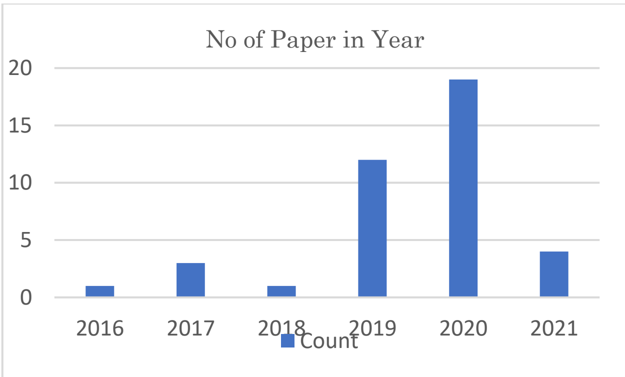

Fig. 2-2. Number of Papers in Year

3.3 Publication Sources

Of the 42 primary studies selected, the highest publications were from IEEE, with a total of 16. This is followed by Science Direct with 15 and Web of Science with nine publications. The figure below illustrates the number of selected primary studies in this study. The figure also shows the number of selected primary studies grouped by place of publication. It can be seen that the most selected primary studies were chosen from the IEEE digital library, followed by Science Direct, and Web of Science. There are more sources that can be retrieved regarding ML articles but since this paper is limited to these three sources (WoS, ScienceDirect and IEEE), hence, it will be that way due to the limitation underlined by the author for this study.

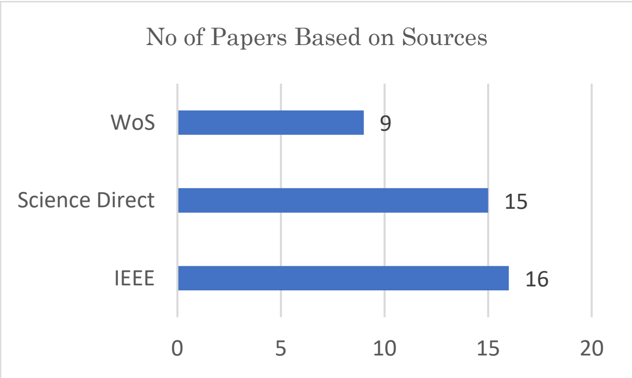

Fig. 2-3. Number of Papers Based on the Sources

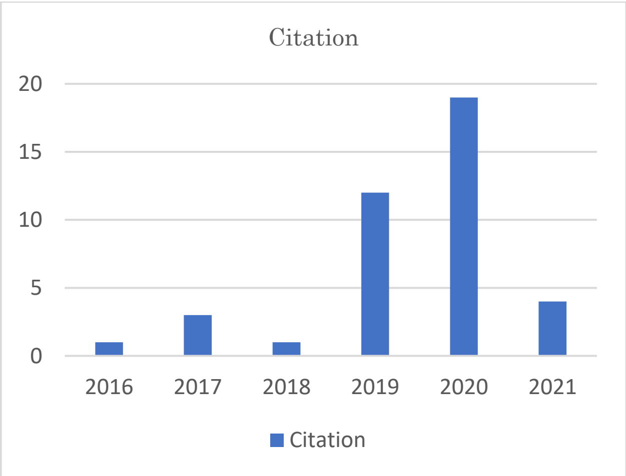

Fig. 2-4. Number of Citation in Year

The above figure shows the citation numbers in years. The trend increased starting from 2016 but decreased slightly in 2018 and continued to increase exponentially in 2019 and 2020. The number of citations in 2021 was only retrieved up to the month of May. From the trend, it shows that the demand for ML studies has become a promising technology due to its functionality and benefits to the industry. According to [48], not by accident, ML initiatives in 2015 were more likely to fail than those in 2019, and the year 2018 marked a turning point in Natural Language Processing (NLP). Basically, the year was all about building on it and moving the field to new levels of excellence in 2019. Due to interrelations between NLP and ML, there is no doubt that 2019 was a starting point as the exponential increment happened in ML papers.

3.4 Quality Assessment Result

Table 2-1 shows the quality assessment form that was conducted to assess the research paper according to the criteria. The basic criteria were compulsory to be passed and true because they are a controlling element for the paper to be accepted. For the specific criteria, the result was accepted if the number of "yes" is equal to three (3) or greater than that. There were 45 articles included in the Quality Assessment, with five of them receiving a "no" and removed after failing the assessment score. There are also control criteria in basic criteria that required both answers to be "yes" for the article to be accepted. However, the criteria in specific criteria such as "measurement suitable?" were a bit tough and tended to get biased, so three "yeses" in other criteria minimized it. The result from the quality assessment confirmed that only 40 articles were included. Despite the fact that all five specific criteria appeared to be important in the assessment, the authors decided that having three of them were very solid and significant, and this represented a majority with sixty percent compliance with the specific criteria. Therefore, after eliminating the "no" result, it was confirmed that forty (40) articles were included as valid.

TABLE 2-1. QUALITY ASSESSMENT FORM 1

Basic Criteria	[1]	[2]	[3]	[4]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	[15]	[16]	[17]
RQ clearly stated?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obtained data able to answer RQ?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Specific Criteria															
Sampling relevant for RQ?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample represent population?	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	No
Measurement Suitable?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Nonresponse bias low risk?	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	No
Statistical analysis answer RQ?	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
a) **Result**	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No

3.5 Type of Industry

Based on the study, there are various types of industries that have deployed ML methods in their prediction models. From the top ten (10) summary in Table 4-1 as shown in Section 3.6, the most accurate model is from the steel industry, followed by the automotive and bioinformatics industries that applied ML techniques in their production systems. Among the five (5) that have the highest numbers of deployed ML techniques in sequence are manufacturing, cloud, petroleum, automotive, and software. From the figure, various industry types have adopted ML in their predictive analytics and the subject of prediction also varied depending on the type of product produced in their production line. For example, in the steel industry, "fault" means that a defect is found on the steel, and the prediction model will focus on how it can benefit them in minimizing the defects. This is also to answer Q3 which is "What type of industry adapts the failure prediction model using ML technique?" The outcome is predicted to vary in proportion to technological advancements, owing to AI's widespread application in almost every facet of life. The overall type of industry in this study can be expressed by Fig. 3.5-1. This number is expected to rise over time as a result of AI adoption in various industries and the Natural Programming Language (NPL) used with it [48]. To answer Q3, among of the top 5 industries were Manufacturing, Cloud, Petroleum, Automotive and Software. The conclusion seems to be broad due to the increased understanding and advantages of machine learning, and it is not industry-specific.

TABLE 2-2. QUALITY ASSESSMENT FORM 2

Basic Criteria	[18]	[19]	[20]	[21]	[22]	[23]	[24]	[25]	[26]	[27]	[28]	[29]	[30]	[31]	[32]
RQ clearly stated?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obtained data able to answer RQ?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Specific Criteria															
Sampling relevant for RQ?	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample represent population?	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Measurement Suitable?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	No
Nonresponse bias low risk?	Yes	Yes	Yes	Yes	No	Yes	No	Yes	No	Yes	No	Yes	Yes	Yes	Yes
Statistical analysis answer RQ?	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	No	Yes	Yes	Yes	No
a) **Result**	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	No	Yes	Yes	Yes	Yes

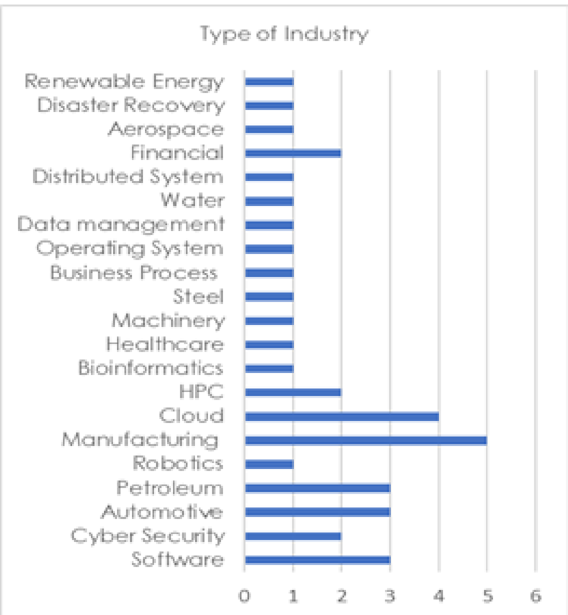

Fig. 2-5. Type of industry using ML technique

3.5 ML Method Used in Individual and Ensemble Prediction Model

In this section, various individual prediction models that were employed in the primary studies and were chosen for inclusion in the article are evaluated, and the best model in each research is found. These are the questions that follow: Each fault prediction model uses different data, as shown in Figure 2-6 in Section 3.6. According to the top ten summary table in Table 4-1, various ML techniques were used depending on the "what" to predict in any of the industry. The most accurate recorded used LSTM which predicted dynamic behavioral changes in the industry of steel. This method is considered as an individual prediction model since it consists of a single technique to get the most accurate in predicting the failure. From a theoretical perspective, RNNs can handle long-term dependencies well. The initial form of such problems is best solved using carefully selected parameters. However, it has proven difficult to learn these patterns with RNNs. As a result, LSTM was developed to tackle long-term reliance issues, and as a conscious design choice, LSTM helps to mitigate long-term dependency issues. This is followed by Convolutional Neural Network (CNN) and Decision Tree (DT) that are used in the automotive industry to detect welding defects. This is considered as an ensemble since two methods are combined in one model and produce high accuracy, as mentioned in Table 4-1. Based on Fig. 3.5-2 below, the top five (5) ML methods used in the prediction model in sequential order are SVM, RF, DT, LR, and LSTM. This is to answer Q1 which is “What are the ML methods that are being used to perform failure prediction in production?”. This question wants to brief an overview on what and which techniques of machine learning used in production environment. Q1 also give a glance on popularity technique, and which one chose for prediction in production because not all technique suits for all industries, but which type of industry use what kind of technique. Despite being the most accurate, LSTM seems to have no popularity among the combinations with supervised type of ML, which shows that SVM is the top consumed by industry players according to Fig. 3.5-2. In short, there were many varieties of ML techniques used by the industries and it depends on the suitability and practicality of the data involved in the production. However, LSTM is still promising in terms of the accuracy result, and it is expected to increase in usage.

TABLE 2-3. QUALITY ASSESSMENT FORM 3

Basic Criteria	[33]	[34]	[35]	[36]	[37]	[38]	[39]	[40]	[41]	[42]	[43]	[44]	[45]
RQ clearly stated?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obtained data able to answer RQ?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Specific Criteria													
Sampling relevant for RQ?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample represent population?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes
Measurement Suitable?	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nonresponse bias low risk?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Statistical analysis answer RQ?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
a) ***Result***	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

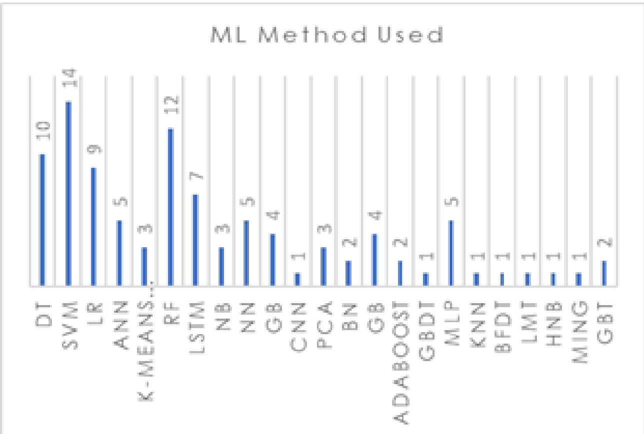

Figure 2-7: ML method used

3.6 Accuracy

The results of the table are summarized in the following text: In the study presented in Table 4-1 below, there were nine models of maintainability, and the model that exhibited the greatest accuracy when predicting the failure measures is featured. One must choose the optimal model by using prediction accuracy evaluation metrics such as prediction error and precision for the individual prediction models that are utilized in each investigation. The most suitable model is recommended as a guide for each investigation. From Table 4-1 below, it can be seen that the most accurate prediction is using LSTM, with a result of 99.92%, followed by 99% for Convolutional Neural Networks (CNN), DT, and NB. The rest is shown in Table 4-1. This is to answer Q2, which is "What is the accuracy level, and which is the best technique for applying ML in failure prediction?". Which Score Is the Best? If it is attempting to solve a classification issue, the optimal score is 100% accuracy. When solving a regression issue, the optimal score is 0.0 error. These are unachievable upper or lower bounds.The result shows top 5 of the most accurate were RNN, CNN, DT,NB,NN and MLP-ANN, LS-SVM. According to Table 4-1 below, the subject of prediction is noted to answer Q4 "What is the subject of failure employed in the failure prediction model in production?". The focus of using ML technique in forecasting the defect for sure containing varies of subject depending on the type of industry. For example, in Steel Industry, defects in their product or material could be the subject for failure employed in failure prediction. It is possible to employ failure analysis to uncover patterns and establish the likely causes of failures It may be used to spot manufacturing and design flaws, forecast failures in the future, and even enhance a component's performance.

Data on equipment use is critical in determining its condition. The subject of failure employed can be notified in the "Prediction" column in Table 4-1 and it is varied from "Dynamic behavioral changes", "Welding defects of hairpins", "Protein-coding genes", "Hardware failures", "Water Saturation", "Node Failure", "Structured Query Language (SQL) Injection Attack (SQLIA)", "Electric motor overcurrent", "To detect signals for potential failures", and "Centrifugal pump". There is no significant outcome from this diversity of subjects, and it shows all the top ten accurate techniques are from a variety of subjects. According to the top ten summary of ML techniques used for failure prediction, most of them were unsupervised ML techniques and seemed to dominate the techniques when compared to only a few of them that were supervised. This shows the unsupervised technique seems promising and reliable in performing failure prediction using ML, and this has been proven with the LSTM technique, which was the most accurate compared to others.

TABLE 2-4. TOP 10 SUMMARY OF ML TECHNIQUE USED IN FAILURE PREDICTION

Reference	ML Method	Industry	Prediction	Description of the data applied for failure prediction	Accuracy
[21]	LSTM(RNN)	Steel	Dynamic behavioral changes	Timely identify rare events based on historical data and predict dynamic behavioral changes in the manufacturing settings.	99.92%
[4]	Convolutional Neural Networks (CNN), DT	Automotive	Welding defects of hairpins	Preprocessing of the 3D data and the modeling of the network	99%
[15]	NB	bioinformatics	Protein-coding genes	Apache Spark framework for efficient prediction of genes in the genome of eukaryotic organisms	99%
[19]	NN	HPC	Hardware failures	introduce the probability of unnecessarily triggering checkpoints (UC) as a metric to evaluate the quality of node-level failure	99%
[24]	MLP-ANN, LS-SVM	Petroleum	Water Saturation	Capture the non-linear behaviors and high-dimensional complex relationships among field log data variables	99%
[31]	SVM,BN, Best-First Decision Tree (BFDT),NB, DT, Logistic Model Tree (LMT), HNB	Distributed System	Node Failure	Blends anomaly-based and signature-based techniques to identify multi-tier failures	98.80%
[10]	SVM	Cyber Security	Structured Query Language (SQL) Injection Attack (SQLIA)	Machine Learning (ML) predictive analytics provides a functional and scalable mining to big data in detection and prevention of SQLIA	98.60%
[14]	RF, GB, LR, MLP, GNB, and Linear discriminant	Manufacturing	Electric motor overcurrent	Model was trained to detect whether the motor has been running on overcurrent in the past 10 minutes	98.60%
[23]	RF, GB, MLP, SVM, XGBoost (GBDT)	Manufacturing	To detect signals for potential failures	Machine learning models in the system calculate the optimum values according to the changes in the input parameters resulting from instantaneous measurements automatically	98.20%
[39]	SVM, MLP	Petroleum	Centrifugal pump	Raw sensor data, mainly from temperature, pressure and vibrations probes, are denoised, pre-processed and successively coded to train the model	98.20%

4.0 CONCLUSION

Lately, we have seen an upswing in research on the ways in which producers handle output uncertainty. This SLR was created with the purpose of collecting, documenting, and classifying past studies that investigate the adaptability of failure prediction to the impact of the production environment using machine learning techniques.

Despite searching several databases and sending emails to the article writers, numerous articles could not be found using this SLR. According to the study, the following four themes emerged: (1) the variety of ML techniques, industries, and failure prediction; (2 of 4 themes discovered), and (2) various methods of processing data, industries, and failure prediction (2 of 4 themes discovered).

Accuracy is a significant theme, but it depends on the industry. Although using unsupervised technology is underused due to factors such as the need that does not need it, there are scenarios where it is particularly useful. These findings may enable manufacturers and their customers to establish appropriate policies that represent manufacturers' and customers' capabilities and needs, and which can help strengthen manufacturers' and customers' adaptability strategies.

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