

**NEURAL NETWORK-BASED PATTERN RECOGNITION
FOR STATISTICAL PROCESS MONITORING**

BY
ZAKARIYE ALI

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In Partial Fulfillment of the
Requirements for the Degree of

MASTER OF SCIENCE

In

APPLIED STATISTICS

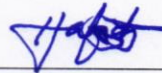
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DHAHRAN- 31261, SAUDI ARABIA
COLLEGE OF GRADUATE AND INTERDISCIPLINARY STUDIES

This thesis, written by **ZAKARIYE ALI** under the direction of his thesis advisor and approved by his thesis committee, has been presented and accepted by the Dean, College of Graduate and Interdisciplinary Studies, in partial fulfillment of the requirements for the degree of **MASTER OF SCIENCE IN APPLIED STATISTICS**.



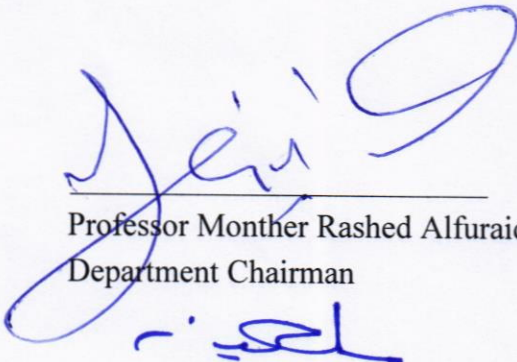
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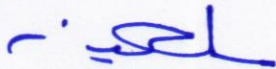
Dr. Mohammad Hafidz Omar (Member)



Dr. Zaid Sawlan (Member)



Professor Monther Rashed Alfuraidan
Department Chairman



Professor Suliman S. Al-Homidan
Dean of Graduate Studies

Date



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To My Parents

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LIST OF ABBREVIATIONS

ANN: Artificial neural network

CCPR: Control chart pattern recognition

CUSUM: Cumulative Sum

CNN: Convolution Neural Network

CYC: Cyclic

DS: Down Shift

DT: Down Trend

EWMA: Exponentially Weighted Moving Average

FNN: Feedforward Neural Network

Hybrid CNN-RNN: Hybrid Convolution Neural Network and Recurrent Neural Network

MCUSUM: Multivariate Cumulative Sum

MEMWA: Multivariate Exponentially Weighted Moving Average

NOR: Normal

US: Upper shift

UT: Upper Trend

RAM: Runger, Alt and Montgomery

RNN: Recurrent Neural Network

SPC: Statistical process control

ABSTRACT

Full Name : Zakariye Ahmed Ali

Thesis Title : Neural Network-Based Pattern Recognition for Statistical Process Monitoring

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Statistical Process Control (SPC) is extensively employed for quality monitoring and controlling industrial processes. Classical methods for Control Chart Pattern Recognition (CCPR), methods, rely on assumptions such as normality that may not hold in practical world. These limitations reduce their competence in identifying patterns, especially in complex or non-Gaussian data contexts. This study focuses on handling these challenges through the use of neural network-based models. The proposed strategy aims at enhancing the pattern recognition accuracy and detect shifts for abnormal processes under varying process conditions.

The investigation starts with an extensive and bibliometric analysis of CCPR studies, identifying trends regarding neural network applications, recognizing prevalent model architectures, and revealing significant research deficiencies, e.g., data imbalance, computational limitations, and the absence of standard benchmarks. Following these observations, several neural network models including Feedforward Neural Network (FNN), Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), and hybrid CNN-RNN are developed and evaluated on six common control chart patterns using

simulated as well as real datasets. All these models are tested under normal and non-normal distributions (covering gamma, t, and log-normal). The analysis revealed that FNN is the most accurate and robust network model for non-normal distributional setups, whereas the hybrid model is best in identifying sequential patterns.

In order to deal with multivariate monitoring, a novel integration of the Multivariate Cumulative Sum (MCUSUM) control chart and neural networks is also proposed. The hybrid technique assimilates MCUSUM's sensitivity to small shifts with the learning capability of neural networks, resulting in improved detection of abnormal process behavior under asymmetric and non-normal conditions. Overall, the research presents an efficient and robust framework for CCPR, deriving real-world solutions for modern industrial quality control systems.

ملخص الرسالة

الاسم الكامل: زكريا أحمد علي

عنوان الرسالة: التعرف على الأنماط القائم على الشبكات العصبية لمراقبة العمليات الإحصائية

التخصص الرئيسي: الإحصاء التطبيقي

تاريخ الدرجة العلمية: أبريل ٢٠٢٥

طرق ضبط الجودة الإحصائية تم تطبيقها على نطاق واسع في معظم وتستخدم في التحكم الإحصائي في العمليات المجالات الصناعية. لمراقبة الجودة و الحفاظ عليها. الطرق التقليدية لمخططات ضبط الجودة الإحصائية تعتمد على عدة افتراضات ، مثل تبعية البيانات للتوزيع الطبيعي، قد لا تتحقق هذه الافتراضات عمليًا. تُضعف هذه القيود من كفاءة مخططات ضبط الجودة الإحصائية في تحديد الأنماط، لا سيما في سياقات البيانات المعقدة أو غير الطبيعية. تُركز هذه الدراسة على تخفيف هذه التحديات من خلال دراسة نماذج قائمة على الشبكات العصبية بهدف تحسين دقة التعرف على الأنماط واكتشاف التحولات في العمليات غير الطبيعية في ظل ظروف عملية متفاوتة. يبدأ البحث بتحليل شامل و ببيومتری للدراسات، وتحديد الاتجاهات المتعلقة بتطبيقات الشبكات العصبية، والتعرف على هياكل النماذج السائدة، وكشف أوجه القصور البحثية الهامة، على سبيل المثال، عدم توازن البيانات، والقيود الحسابية، وغياب المعايير القياسية. وبعد هذه الملاحظات، تم تطوير العديد من نماذج الشبكات العصبية (الشبكة العصبية ذات التغذية الأمامية، والشبكة العصبية التلافيفية، والشبكة العصبية المتكررة، والهجينة) وتقييمها على ستة أنماط شائعة لمخططات التحكم باستخدام مجموعات بيانات محاكاة وحقيقية. تم تقييم جميع هذه النماذج من خلال التوزيع الطبيعية وغير الطبيعية مثل توزيع جاما، توزيع تي، التوزيع الطبيعي اللوغاريتمي حيث أظهرت النتائج أن مخططات ضبط الجودة الإحصائية التي تعتمد على الشبكة العصبية الأمامية كانت الأكثر دقة ومتانة، بينما كان النموذج الهجين هو الأفضل في تحديد الأنماط المتسلسلة. لتحسين أداء المراقبة متعددة المتغيرات، في البحث قمنا باقتراح دمج جديد لمخطط التحكم متعدد المتغيرات للمجموع التراكمي والشبكات العصبية. تدمج هذه التقنية الهجينة حساسية مخططات التحكم متعدد المتغيرات للتحولات الصغيرة مع قدرة الشبكات العصبية على التعلم، مما يُحسن من اكتشاف سلوكيات العمليات غير الطبيعية في ظل

ظروف غير متماثلة وغير طبيعية. بشكل عام، يُقدم البحث إطارًا متينًا وذكياً للطرق الكلاسيكية للتعرف على أنماط مخططات التحكم، مستمداً حلولاً عملية لأنظمة مراقبة الجودة الصناعية الحديثة.

CHAPTER 1

INTRODUCTION

1.1 Background of the Study

Statistical Process Control (SPC) is a basic technique under quality management, utilized to regulate and monitor process performance through monitoring and control. Control charts are among the most vital tools in SPC and are helpful in the detection of trends in process behavior over time. Traditional pattern detection in control charts is normally performed manually and is thus time-consuming mainly in sophisticated and computer-based manufacturing settings.

As industrial processes advance and generate more intricate patterns of data, traditional techniques cannot detect subtle or concurrent anomalies accurately. Under such circumstances, Control Chart Pattern Recognition (CCPR) has become indispensable for the detection of typical process shifts, trends, and cyclical patterns signaling quality issues. Neural Network (NN)-based models offer a solution, as they can learn and classify advanced patterns automatically, particularly in non-normal distributions that are common in real-world processes.

This study proposes a neural network-based CCPR system that can accurately detect six common control chart patterns such as random, shift up, shift down, trend increase, trend decrease, and cyclic patterns, especially for non-normal distributions such as gamma, t, and log-normal.

1.2 Problem Statement

Traditional CCPR systems rely on assumptions like normality, stationarity, and easily separable patterns, which do not actually exist. Manual pattern recognition is not reliable, and classical statistical models are poor in handling skewed or heavy-tailed data. Furthermore, contemporary CCPR models mostly ignore challenges posed by overlapping patterns or real-time detection in real-world industrial environments. A robust, adaptive, and automatic CCPR model with optimal performance under non-normal data and high classification precision is thus required—particularly one that works well under such conditions.

1.3 Study Objectives

The main goals of this research are:

- Developing artificial neural network model and training ANN model to classify six common control chart patterns i.e. random, shift up, shift down, trend increase, trend decrease, and cyclic to ensure process stability.
- Evaluating the performance of ANN model based on measures like classification accuracy and confusion matrices.
- Developing robust control charts for cases under non normal distribution such as log-normal, gamma and t distribution.
- Utilizing the proposed approaches on a real-world scenario (e.g. healthcare, business, engineering) for monitoring and classifying control chart patterns to get timely detection of deviations and immediate quality control responses.

1.4 Research Questions

- Can a correctly classify six common SPC patterns for six different non-normal distributions using an ANN model?
- Do neural network models perform differently from traditional SPC methods under heavy-tailed and skewed distributions?
- Which topology of the neural network is most effective for CCPR in real-life, non-ideal data environments?
- Can integrate MCUSUM and Neural network enhance the detecting of shifts?

1.5 Significance of the Study

This research contributes to quality control studies by proposing a neural network-based CCPR method that addresses major problems of non-normality and pattern overlap. It promotes automation and accuracy in process monitoring and assists in industries in early anomaly detection, ultimately enhancing production quality and reducing operation risks. The study also contrasts neural architecture, which will guide future model choice and design.

1.6 Structure of the Thesis

Chapter One: Research background, problem statement, objectives, significance, and scope of study.

Chapter Two: Presents a comprehensive literature review of CCPR techniques using neural networks, highlighting their development and areas of research that need to be addressed.

Chapter Three: Compares several models of neural networks for CCPR in normal and non-normal data environments by simulation and real data studies.

Chapter Four: Proposes a robust neural network-based control chart for Multivariate control chart.

Chapter Five: Offers the thesis conclusion in terms of summary of findings.

CHAPTER 2

SYSTEMATIC AND BIBIOMTRIC ANALYSIS FOR CONTROL CHART PATTERN RECOGNITION

This chapter presents a comprehensive overview of the literature available on Control Chart Pattern Recognition (CCPR) with a specific focus on neural network-based methods. The review begins by outlining the theoretical background and history of CCPR in Statistical Process Control (SPC) and then follows it up by outlining the methodology of literature selection and subsequently presenting a systematic comparison of some of the recent research contributions in the field. Significant issues such as classifier architecture, performance metrics, data handling approaches, and industry applications are covered. Bibliometric analysis of scholarly trends and research impact is also included in the chapter. Finally, research gaps identified are consolidated to develop the rationale of the research work in subsequent chapters.

2.1 Introduction

Control Chart Pattern Recognition (CCPR) is an important part of the general Statistical Process Control (SPC) framework to achieve early detection of process abnormality and deviation from normal operating conditions. Conventional SPC techniques like Shewhart charts, Cumulative Sum (CUSUM) charts, and Exponentially Weighted Moving Average (EWMA) charts have been extensively used for that purpose. While effective in monitoring process stability, these methods struggle with complex, overlapping, and concurrent

control chart patterns (CCPs), making them less suitable for modern industrial environments characterized by high variability and automation [1].

With the arrival of artificial intelligence (AI) and machine learning, Neural networks subsequently emerged as effective models for advancing CCPR. Early research generally focused on Artificial Neural Network (ANN) models with straightforward feedforward networks using backpropagation algorithms [2]. These models required substantial computing feature engineering and data preprocessing, which limited scalability and automation [3].

Further developments involved hybrid methods, where neural networks were combined with other optimization techniques like genetic algorithms [4], fuzzy logic [5], and swarm intelligence [6] to enhance classification accuracy and model adaptability across diverse control patterns. More recently, deep learning architecture, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) has shown remarkable performance in CCPR by automatically extracting hierarchical features and detecting sequential dependencies in process data from [7]; [8]. Other advanced models incorporate self-organizing spiking neural networks for added robustness and adaptiveness, proposed in the works of [9] and ensemble deep learning techniques further promote robustness or adaptability [10].

Recent studies have increasingly focused on developing real-time and autonomous CCPR systems. Research has investigated the use of ensemble learning to achieve better generalization, [11], while self-organizing neural networks have been used to adapt to changing manufacturing conditions, [12]. Probabilistic neural networks together with Bayesian inference techniques have also been developed to model uncertainty in process

monitoring, [13] [8]. Other recent works have also involved hybrid models that incorporate deep learning with statistical approaches, such as support vector machines and wavelet transformation [4]; [14], for improving the classification precision.

Despite these, some challenges remain. Data imbalance hinders classification performance in some instances, especially when real-world applications contain much more normal process conditions compared to abnormal ones [15]. Another challenge is that the deep learning models under discussion have high computational requirements, making real-time implementation difficult in resource-constrained environments. Other concerns include the interpretability of neural networks; black-box models again provide limited trust and thus limited adoption in industrial settings [16]. Optimization techniques such as evolutionary algorithms and reinforcement learning have been explored to address these challenges, although further research is needed for industrial adaptation [17]; [18]; that have been proposed, though additional research is necessary to refine these methods for practical use. Several review studies have addressed the development and methodologies of neural networks for CCPR. For example, [19] proposed a conceptual framework that categorizes CCPR techniques based on data assumptions, input structures, and model architectures. [20], discussed the application of neural networks to SPC, addressing their capability to detect mean and variance shifts, besides dealing with correlated process data. [21], conducted a systematic review on concurrent CCP recognition, detailing the shift to more machine learning approaches because of their better performance in classification and considering overlapped patterns. [22] conducted a general review on the applications of ANN in pattern recognition, underlining the role of hybrid models and deep learning in improving the performance of classification. More recently, other reviews such as [23]

considered the trends for ensemble learning, transfer learning, and real-time deployment of deep learning-based CCPR.

2.2 Methodology

This study employs a structured methodology informed by systematic review principles and bibliometric analysis techniques to ensure rigorous literature selection and evaluation. The methodology consists of four main stages from PRISMA such as searching, inclusion criteria, exclusion criteria, final selection and bibliometric analysis.

2.2.1 Identification (Searching Strategy)

The literature search was conducted using academic databases such as Web of Science. The search terms included combinations of keywords such as “control chart pattern recognition,” “neural networks,” “deep learning,” “artificial intelligence,” and “statistical process control.” The initial search retrieved 253 papers published between 1993 and 2024.

2.2.2 Inclusion Criteria

The following criteria were applied to ensure the relevance of selected studies:

- I. Papers must focus on neural network-based approaches for CCPR.
- II. Studies should provide performance evaluation of CCPR models.
- III. Research should discuss preprocessing techniques implementation of CCPR.
- IV. Only peer-reviewed journal articles, review and conference papers were considered.

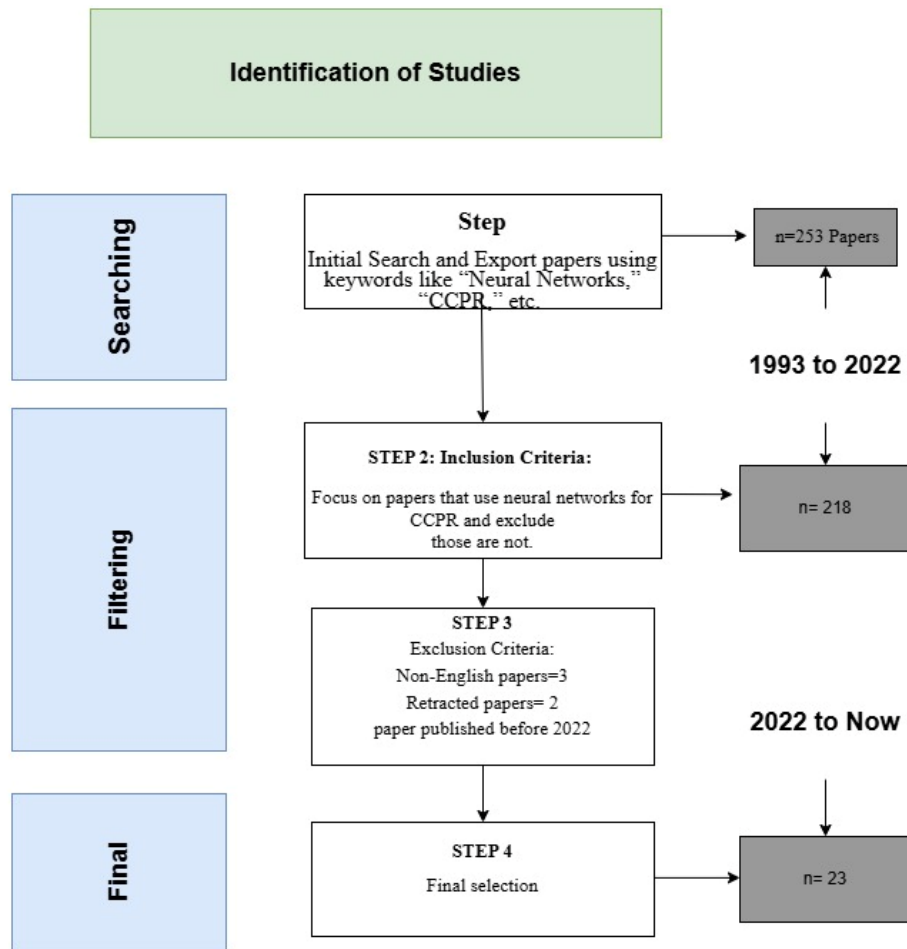


Figure 2.1: Identification papers

2.2.3 Exclusion Criteria

To maintain the quality and relevance of the review, the following exclusion criteria were applied:

- I. Papers not written in English (n = 3).
- II. Retracted papers or studies with insufficient methodological descriptions (n = 2).
- III. Duplicates or papers that did not explicitly focus on CCPR using neural networks.
- IV. Exclude paper published before 2022 (n=213)

2.2.4 Final Selection

After the inclusion and exclusion criteria were applied, 23 papers remained to be considered for review. The final dataset encompasses studies that cover a wide range of neural network models, preprocessing techniques, and optimization strategies for CCPR. The flowchart for selection, Figure 2.1, illustrates a PRISMA-based flowchart showing the systematic filtering of research papers.

2.3 Systematic analysis

Table 2.1 presents a synthesized overview of recent CCPR research using neural network, outlining model types, evaluation metrics, pattern type involved, accuracy percentage, and industrial applications.

Authors	Classifier	Evaluation techniques	Data Handling Techniques	Type of patterns	Accuracy rate	Applications in Industries
[24]	PCA	Recognition rates, and false positives.	Feature extraction	Concurrent patterns	96.3%	manufacturing.
[25]	Random Forest	Recognition accuracy, ARL and SRL for dynamic data.	synthetic dataset, feature extraction.	simple patterns	97.96%	Chemical manufacturing

[26]	1D-CNN	Hamming Loss, Jaccard Index, precision, recall, F1-score.	End-to-end feature extraction	single and Concurrent patterns		manufacturing
[27]	Bag-of-Words model	Accuracy, early warning systems.	Feature extraction			Multivariate industrial
[28]	1D CNN + SVM	The overall accuracy	AR (1) noise modeling, Monte Carlo simulations, feature extraction	simple patterns	89.02%	Industries with auto-correlated data.
[29]	1D and 2D CNN	Classification accuracy	data augmentation	simple patterns	10% improvement, imbalanced	Multivariate industrial.
[30]	CNN	Precision, recall, F1-score accuracy	SMOTE algorithm, multi-feature fusion.	single and Concurrent patterns	(99.7%).	manufacturing
[31]	FFNN	confusion matrix, CoDa	Isometric Log-Ratio (ilr)	simple patterns		Multivariate Industrials

		RMSE for error	transformation for CoDa preprocessing.			
[32]	Ensemble classifier integrating decision trees, ANN, SVM, and k-NN.	Classification accuracy	Feature selection, synthetic data.	simple patterns	99.55%,	Manufacturing
[33]	CNN with AdaBoost	Recognition accuracy	Signal resizing, Bayesian optimization	simple and mixed abnormal patterns	99.78%	Manufacturing
[34]	Decision tree	classification under optimal parameters, cross-validation for robustness.	Pattern segmentation and moving window.	simple patterns		Manufacturing
[35]	Hybrid CNN-LSTM	Average accuracy	feature decomposition	single and Concurrent patterns	99.83%	Manufacturing

[36]	Zero-Shot Learning (ZSL) with Multiscale Ordinal Pattern Features.	Recognition accuracy of evaluated Type I & II errors.	Attribute Transfer Framework, Monte Carlo simulations for CCP data.	single and Concurrent patterns	98.89%	Manufacturing
[37]	Ensemble learning with BP, ELM, PNN, and SVM	Recognition accuracy of misclassification reduction for normal patterns.	SMOTE for balancing datasets.	simple patterns	97.31%	Manufacturing,
[38]	CNN	Accuracy, and classification metric	Multi-scale time series slicing, distance mode profile (DMP).	simple patterns		Body-in-White (BIW) production.
[39]	BiLSTM	G-mean, sensitivity, specificity, rolling window-	Mix Ratio Data Simulation (MRDS), cost-	simple patterns		Biomanufacturing & wafer industries

		based stability metrics.	sensitive learning for imbalanced data.			
[36]	WOP with ensemble classifiers	Recognition accuracy	Feature extraction	simple patterns	94.31% and 99.88%	Manufacturing
[40]	CNN combined with SVR	Detection of type-I censored data with the Weibull model.	Residual monitoring, sliding time windows.			Industries
[41]	LSTM	ARL	Monte Carlo simulations			Car manufacturing (wheel alignment).
[42]	RNN-LSTM	Average Target Pattern Run Length (ATPRL), Detection Average	Synthetic data generation, window size sensitivity.	single and Concurrent patterns		Manufacturing

		(DA), Average False Alarm (AFA),				
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Table 2.1: Summaries of Recent Studies For CCPR

2.3.1 Classifiers and Methodological Approaches

The reviewed studies illustrate the evolution from traditional statistical techniques, including Principal Component Analysis, to complex neural network architectures, such as Convolutional Neural Networks, Long Short-Term Memory, and hybrid CNN-LSTM. Ensemble learning approaches integrating multiple algorithms have shown notable improvements in recognition performance like decision trees, ANN, SVM, and KNN ensure significant improvement in recognition accuracy. This is shown by the works of [32] and [37].

2.3.2 Evaluation Techniques

A wide range of evaluation metrics has been utilized to comprehensively assess model performance under diverse conditions. Usual measures are recognition accuracy, precision, recall, and F1-score, but also advanced indices are employed, including Hamming Loss, Jaccard Index, Average Run Length, and Average Target Pattern Run Length. Comprehensive metrics are, therefore, suitable for performance evaluations within dynamic and complex data conditions.

Other research focuses on the least rate of misclassification and false positives as well as limiting sensitivity to censored data, hence they are very-articulate in validating their models.

2.3.3 Data Handling Strategies

Various studies employ distinct data preprocessing strategies, from basic feature extraction to advanced techniques such as SMOTE and Monte Carlo simulations. Synthetic data generation overcomes data scarcity issues and enhances model generalization.

Advanced preprocessing approaches also include the recent adoption of such methods as Isometric Log-Ratio (ilr) transformation for compositional data and several feature fusion strategies to boost the robustness and accuracy of the models.

2.3.4 Pattern Types and Model Accuracy

The reviewed literature addresses both simple and concurrent CCP types, with most models reporting accuracy rates exceeding 95%. Such high accuracy reports attest to modern neural network methods' effectiveness to CCPR.

The highest recorded accuracy of 99.83% was obtained using a hybrid CNN-LSTM model by [35]. [30], and [32], obtained impressive accuracy rates of 99.7% and 99.55%, respectively, with CNN and ensemble classifiers.

2.3.5 Industrial Applications

The applications of machine learning (ML) and deep learning (DL) models in Control Chart Pattern Recognition (CCPR) have significantly advanced process monitoring, fault detection, and predictive maintenance in different sectors. In auto manufacturing, Artificial Intelligence (AI)-based approaches such as LSTM-based control charts Yeganeh et al., (2025) and Random Forest model for bivariate autocorrelated processes [30] enhanced real-time anomaly detection and predictive maintenance with control of high-frequency sensor measurements. Similarly, Bag-of-Words (BoW) techniques [27] are applied for multivariate time series (MTS) in optimizing predictive maintenance and anomaly

detection during production. Multi-scale time series classification (TSC) models were presented by [38] for BIW manufacturing defects identification, which constitutes a critical stage in automotive body manufacturing, where early fault detection is essential.

Precision matters in chemical and biomanufacturing industries, so quality control and anomaly identification are dependent on AI-based models. BiLSTM predictive models [39] have been utilized in wafer and biomanufacturing industries with real-time checks and adaptive fault detection. Minor variation detection is also employed with ensemble classifiers [32] in chemical, aerospace, and electronics industries for ensuring stability in high-precision manufacturing operations. Advanced time-series classification (TSC) models Bao et al., (2024) and multi-label CNNs for parallel pattern classification [29] have significantly contributed to improving real-time fault detection and enhancing classification accuracy. Furthermore, decision-tree-based approaches [34] have also been applied to enhance the stability of machining processes through the automatic detection of anomalies as well as the reduction of dependency on human quality control.

Hybrid and ensemble learning have also emerged as promising methodologies in AI-based CCPR studies that yield improved fault classification and pattern detection. Zero-Shot Learning (ZSL) models [36] were suggested to discover novel control chart patterns to eliminate the problem of limited labeled training data. On the other hand, Siamese Neural Networks (SNN) [43] were utilized for pattern recognition in small-sample sizes and utilized for applications in high-performing conditions of low data availability. Ensemble learning-based models (BP, ELM, PNN, SVM) [37] were of higher accuracy to classify complicated control chart patterns with lower misclassification errors. Additionally, machine learning-based Six Sigma methodologies [33] have been explored to enhance the

precision of manufacturing, quality control, and data-driven decision-making. As more industries adopt Industry 4.0 strategies, upcoming research will need to focus on scalability, interpretability, and applicability of these AI models to build end-to-end automated, intelligent quality control systems in modern industrial processes.

2.4. Bibliometric Analysis

Complementing the systematic review, a bibliometric analysis is done to describe research trends, influential studies, and scholarly impact. The following data for bibliometric analysis are included:

2.4.1 Citation and Publication Trends

Figure 2.2 illustrates the publication and citation trends of CCPR research from 2022 to 2025. Both publication volume and citation frequency have increased steadily, indicating growing academic interest in the domain.

While 2022 and 2023 showed relatively stable publication numbers with modest citation growth, 2024 had a tenfold increase in the number of publications with over 50 citations, marking this year as important-most probably a consequence of methodological innovations and successful applications of deep learning models. As of early 2025, a number of publications have already emerged, although the year's overall trend remains undetermined. Since the year is still in progress, it's too early to identify any clear trend. As research continues and new studies emerge, they will contribute to the ongoing development of CCPR advancements.

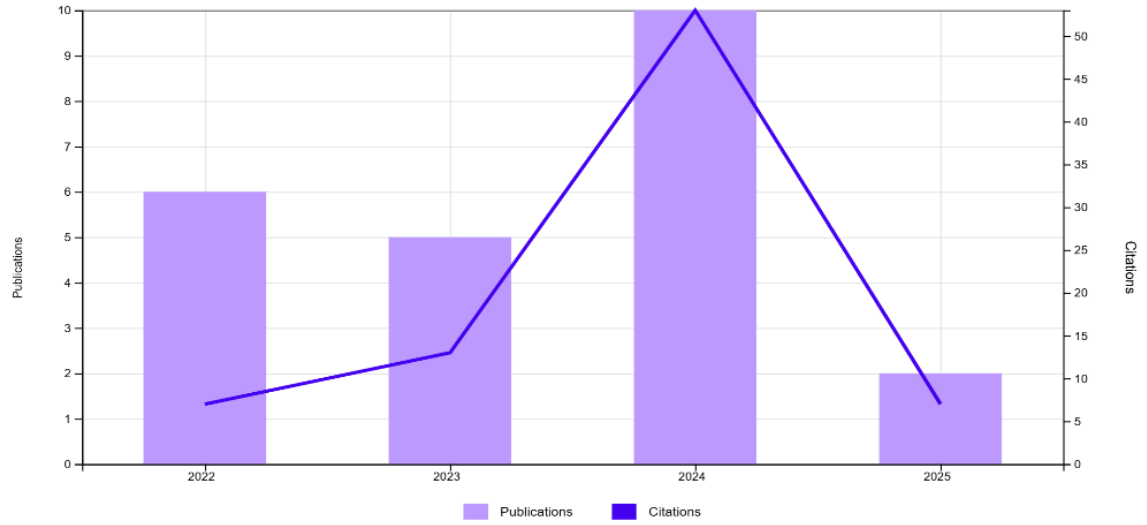


Figure 2.2: Publication and Citation trends

2.4.2 Keyword Analysis

Figures 2.3 and 2.4 present the word cloud and keyword co-occurrence network as a whole highlight the dominant trends of research in machine learning applications, pattern recognition, and quality control. The overall theme is "Control Chart Pattern Recognition" with close relevance to classification, identification, and neural networks. The integration of statistical process control (SPC) with AI-based approaches is evident, reflecting a shift towards predictive, automated, and data-driven fault detection systems from traditional quality monitoring. Key connections among the most frequently occurring terms are illustrated in the following analysis.

- Classification, Identification, and Recognition: The three words are considerably both in figures, so research is mostly all about classifying and identifying patterns on control charts. Though the word cloud graphically evidences their dominance, the network graph shows their frequent co-occurrence with AI techniques.

- Neural Networks and Deep Learning: The terms "neural network," "CNN," "LSTM," and "deep learning" keep appearing and share a common context of inserting AI in the process monitoring. Such words are easily associated with patterns detection, classification, and outliers' detection to facilitate the integration of automated systems of quality control.
- Control Chart and Process Monitoring: The term cloud highlights "multivariate," "monitoring processes," and "control-chart," placing emphasis on ongoing dependence on SPC techniques. The network diagram links control chart pattern recognition to anomaly detection, feature extraction, and machine learning models, depicting a hybrid model.
- Singular Spectrum Analysis and Decomposition: The presence of "singular spectrum analysis" and "decomposition" in the word cloud is an indication that sophisticated signal processing methods are employed in quality control. Such techniques would probably improve feature extraction, time-series analysis, and fault prediction.

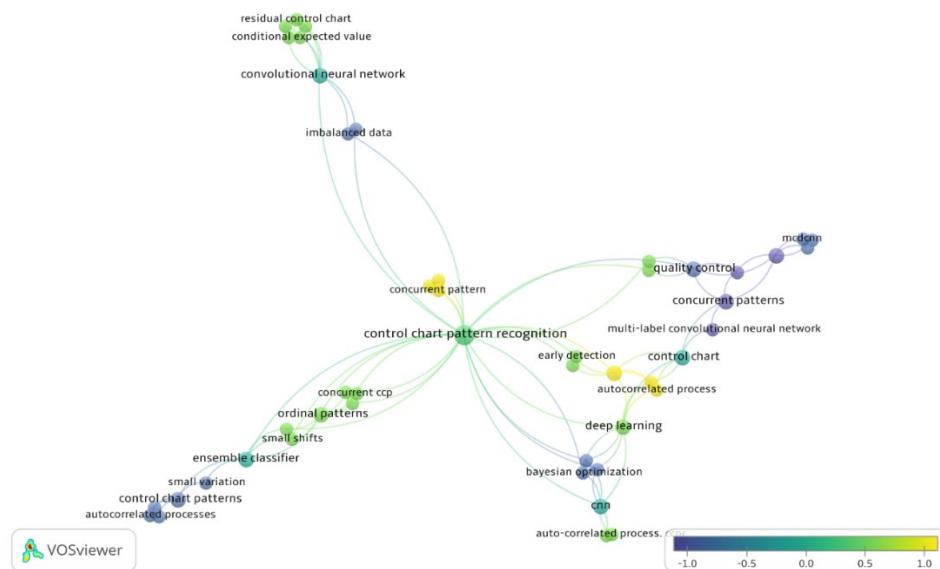


Figure 2.3: Keyword Co-occurrence Network

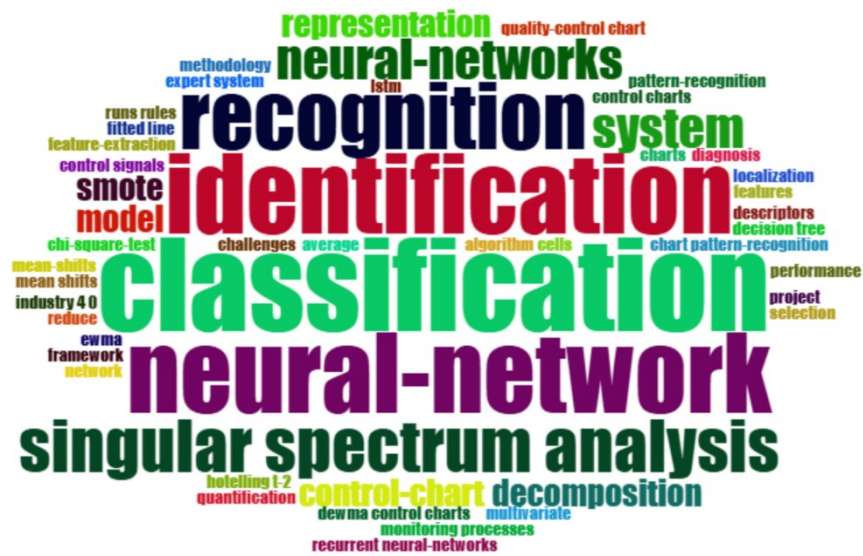


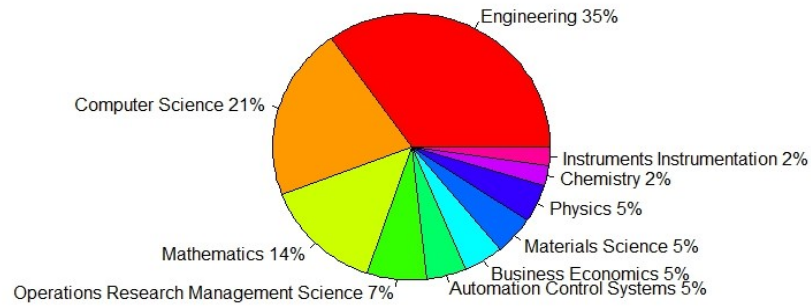
Figure 2.4: Word Cloud

- Optimization and Data Handling Techniques: Terms like "Bayesian optimization," "SMOTE," "mean shifts," and "quantification" indicate a growing interest in optimizing model precision and dealing with unbalanced data sets. Such search terms suggest scientists are striving to improve AI and statistical models to be more precise and reliable for real-time decision-making.

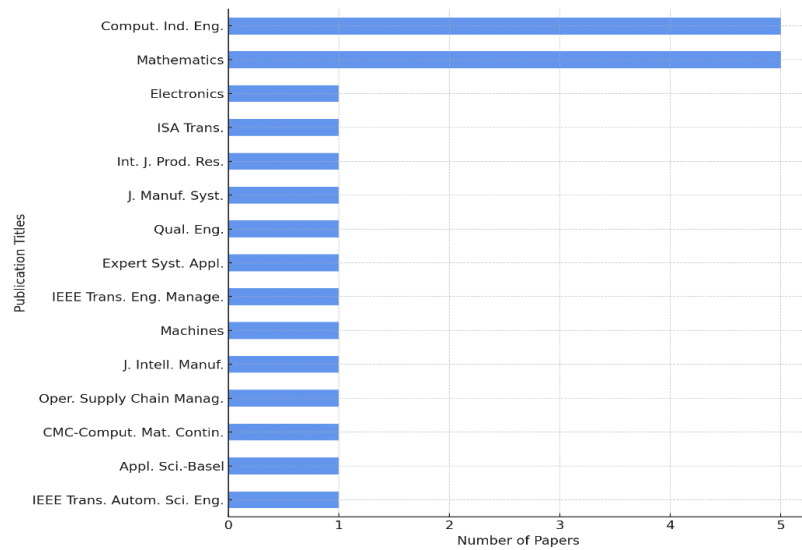
2.4.3 Collaboration and geographical distribution

Figure 2.5 shows the CCPR-related publications in academic journals and research disciplines. The most prominent journals were "Computers & Industrial Engineering" and "Mathematics", each contributing to five publications, reflecting the interdisciplinary nature of CCPR research. Most of the research is rooted in "Engineering" with a share of 35%, followed by "Computer Science" with 21% and "Mathematics" with 14%.

Contributions from areas like "Operations Research & Management Science," "Automation Control Systems," and "Business Economics" point out the wide applicability of CCPR techniques in scientific and industrial fields.



(a) Research areas



(b) Publications

Figure 2.5: a) Research fields and b) Publications

Figure 2.6 maps the geographical distribution of CCPR research contributions in order to represent the global landscape of scholarly activity concerning this field. Contributions are headed by China, with 11 publications, followed by Taiwan with four, and the USA with three, reflecting a high level of emphasis on industrial innovation and technological development in East Asia and North America. Two each from Canada, Colombia, Egypt, and Wales show an increase in CCPR interest from around the world.

Country Collaboration Map

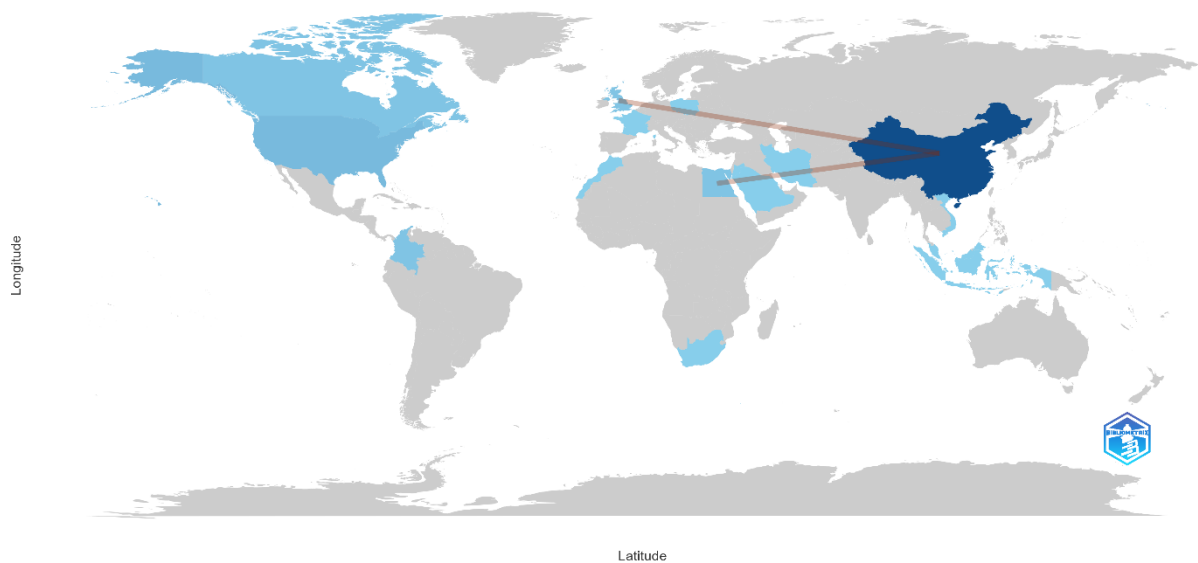


Figure 2.6: Identifies Top Countries In The Field

Single publications come from a wider variety of countries, including Morocco, the UAE, South Africa, Saudi Arabia, Poland, Iran, Malaysia, Jordan, Indonesia, France, and Vietnam. This reflects a wide geographic distribution, highlighting the global relevance and adoption of CCPR methodologies and pointing to the possibility of international collaboration and knowledge sharing.

2.4.4 Type of data

Distribution of data types shows Figure 2.7 used in CCPR studies. A high number of CCPR studies rely on simulation data, up to 54%, reflecting ease in generating big and controlled

data sets for training and testing the models. Real data comes at 23%, indicating practical applications and real-world validations of CCPR models. Interestingly, 14% of the studies use a combination of both simulated and real data to balance model robustness with applicability in the real world. The remaining 9% fall into the "Others" category, probably incorporating synthetic or hybrid data sources, which demonstrates another variant being tried by researchers to handle data availability and quality issues in CCPR research.

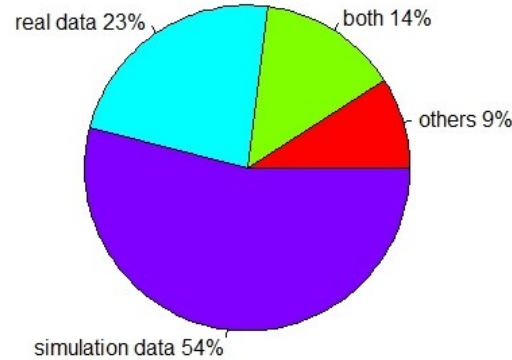


Figure 2.7: Type of data

2.5 Neural Network Architectures in CCPR

The research articles under consideration utilize diverse machine learning (ML) and deep learning (DL) models for enhancing Control Chart Pattern Recognition (CCPR), classification, process monitoring, and anomaly detection. These models can be categorized into broad categories such as deep learning-based models, neural network, machine learning models, and hybrid or ensemble learning models. Each approach offers

distinct advantages and limitations that influence the development and effectiveness of AI-driven quality control systems.

2.5.1 Convolutional Neural Networks (CNN) and Variants

CNNs have been widely applied for pattern detection in control charts because they can extract spatial hierarchical features from raw data. [35] employed a Hybrid CNN-LSTM model to identify mixture control chart patterns (CCPs) in autocorrelated manufacturing, with 99.83% accuracy. [38] reported a CNN guided time-series classification (TSC) model for the identification of anomalous patterns in Body-in-White (BIW) manufacturing, a critical operation in autonomous vehicle assembly. [30] reported a multi-feature fusion CNN for the identification of imbalanced CCPs, with SMOTE utilized for dataset balancing. [26] employed a multi-label CNN-based classification model to improve concurrent pattern detection in industrial quality inspection. Although CNN models demonstrate high classification accuracy, they are computationally demanding and require substantial labeled datasets.

2.5.2 Recurrent Neural Networks (RNN), LSTM, and BiLSTM

RNN-based architecture, especially LSTM and BiLSTM, are widely used in time-series industrial process monitoring since they are capable of learning temporal relationships. [41] employed an LSTM-based control chart model for monitoring bivariate autocorrelated processes in car manufacturing, preventing false alarms and improving fault detection. [39] employed a BiLSTM-based predictive model for anomaly detection during wafer fabrication, applying cost-sensitive learning to unbalanced datasets. [42] applied an RNN-LSTM framework for fault prediction in multivariate time-series data, improving early

warning for quality control. Despite their effectiveness in capturing sequential patterns, deep learning models often involve high computational costs and extended training times.

2.5.3 FNN (FFNN) and Basic ANN

Although deep learning models dominate the scene, FFNN, and ANN models find their application in feature-based classification, ensemble learning, and statistical process control. [31] employed an FFNN model to analyze Hotelling T^2 control charts for compositional data (CoDa) with backpropagation learning and ilr transformation for improved classification. [37] employed BPNN in their ensemble learning model, while [32] employed ANN along with Decision Trees and SVM for hybrid control chart classification. [8]'s CNN-AdaBoost system would have made use of MLP-based weak classifiers, while [24] applied Neural Networks (NN) for their PCA-Wavelet Analysis-based system.

2.5.4 Traditional Machine Learning Models

Decision trees are widely used for simple and rule-based pattern classification. [34] introduced a Decision Tree-based model to enhance machining process stability, demonstrating its efficiency in process anomaly detection automation. [25] employed Random Forest (RF) for bivariate autocorrelated pattern detection, and it was more robust and accurate than SVM and ANN. The models provide interpretable decision-making in real time but are less strong for high-dimensional feature spaces where deep learning-based models are better.

SVM remains an important classifier for high-dimensional pattern recognition in control charts. [28] introduced a 1D CNN-SVM hybrid model to detect autocorrelated process anomalies at a rate of 89.02%. [40] combined CNN with Support Vector Regression (SVR)

for type-I censored data detection. The model demonstrated improved recognition accuracy in detecting small shifts.

2.5.5 Hybrid and Ensemble Learning Models

Ensemble learning involves the use of an ensemble of classifiers to reduce misclassification error and improve generalization performance. [37] presented an ensemble learning model that includes BP, ELM, PNN, and SVM, which significantly improved control chart pattern classification accuracy. [33] introduced CNN with AdaBoost and achieved 99.78% accuracy in abnormal pattern detection with varying windows. [32] applied ensemble classifier combining Decision Trees, ANN, SVM, and k-NN and achieved 99.55% accuracy for X-bar control charts with small shifts. These models offer high efficiency but often necessitate extensive hyperparameter tuning to optimize performance.

To overcome problems in learning from small samples, Siamese Neural Networks (SNN) and

Zero-Shot Learning (ZSL) came into existence. [36] introduced a ZSL model for predicting unforeseen control chart patterns using multiscale ordinal pattern (MOP) features with improved generalizability. [43] applied SNN to the CCPR learning with a small sample size with improved recognition from low-sample sizes.

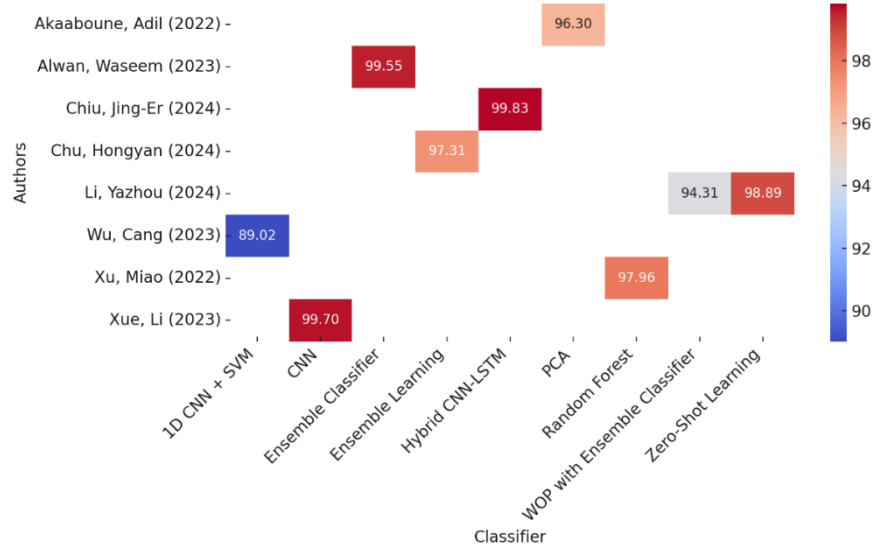


Figure 2.8: Neural Networks and Other Machine Learning Techniques

Figure 2.8 shows Heatmap comparison of performances among various classifiers used in different CCPR studies according to reported accuracy rates from several authors. The highest rate was that for [35] at 99.83% with the Hybrid CNN-LSTM model; this was seconded by [32] at 99.55%, an Ensemble Classifier; and that for [30], at 99.70%, with CNN. The performances discussed herein ensure deep learning approaches along with ensembling to work well while trying to improve classification accuracy.

Moderate performances, within the same range as above mentioned, come from [18] ,97.31% using ensemble learning-and [25], 97.96% using random forest classifiers. On the contrary, [28] reported the lowest accuracy using a 1D CNN combined with SVM at 89.02%, which might indicate some limitations related to classifier generalizability. In turn, [36] shows a relatively high accuracy of Zero-Shot Learning, 98.89%, which denotes the promise of new methodologies in CCPR. The heatmap represents the critical importance of classifier selection for CCPR performance: deep learning architectures along with ensemble methods outperform their counterparts in almost all cases.

2.6. Performance Evaluation Metrics

Figure 2.9 highlights the evaluation techniques most frequently used in CCPR research, reflecting the priorities and methodologies of the field. Recognition accuracy is the most employed measure, indicating its significance in the assessment of model performance. Precision, recall, F1-score, and average run length (ARL) are also utilized as measures for rigorous evaluation of model reliability and robustness.

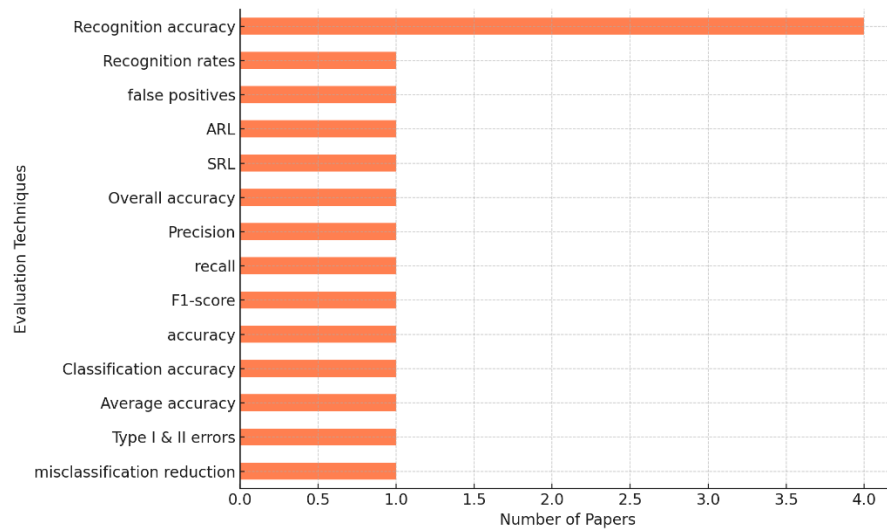


Figure 2.9: Evaluation Performance Metrics

2.7 Identified Research Gaps

While substantial advancements have been achieved in the use of neural network-based control chart pattern recognition (CCPR), there are still some research gaps that limit the practicality, scalability, and robustness of these models. The following research gaps are noted from literature:

2.7.1 Assumptions That May Not Hold in Real-World Conditions

Most research hypothesizes optimal situations, e.g., clean, balanced, and representative data, or stationary process behavior over time. Factory data, however, is noisy, sparse, or

missing data, and processes are dynamic and subject to varying conditions. Assumptions such as stationarity, independence, and uniform pattern behavior often do not align with the complexities of real-world industrial environments.

2.7.2 Data Imbalance

Most real-world industrial datasets are highly imbalanced, containing far fewer examples of abnormal process behavior than normal ones. This results in biased learning, which will create poorly performing classifiers on minority (fault) classes [15]. Various studies have applied techniques like SMOTE or cost-sensitive learning, but these approaches do not eliminate model bias and overfitting on majority classes entirely.

2.7.3 Comparative Benchmark Shortage

There isn't a uniform set of benchmark datasets and testing protocols across literature. It becomes difficult to make objective comparisons among proposed models. Different measures, varying datasets (simulated vs. real), and different experiment configurations introduce ambiguity on which models perform best under analogous conditions. The field can be aided by community-maintained datasets and generally accepted performance metrics for CCPR.

2.7.4 Computational Complexity

Deep learning models such as CNNs, LSTMs, and combinations thereof are typically computationally intensive for training and deployment. This is a challenge for small and medium businesses where availability of resources limits real-time deployment viability. The fact that they need periodic retraining to capture process changes further contributes to the workload.

2.7.5 Limited Model Interpretability and Application data

Most top-performing neural network models are black boxes, providing little explanation for why they make specific predictions [16]. In highly regulated and safety-critical sectors, operator confidence, decision verification, and auditable requirements necessitate interpretability and explainability, and shortage of real data. Despite a growing interest in explanation AI in research, only a limited number of CCPR studies have incorporated interpretable models or post hoc explanation methods.

2.7.6 Generalization and Adaptability

Industrial conditions are dynamic, and process conditions change with time. Static models trained from the past data will generally not extend to new conditions or detect new emerging fault types. Research explores some self-organizing networks and transfer learning, but research on adaptive learning systems that adapt and expand with the process while maintaining performance is limited [4]; [18].

These lacunae suggest that while existing models perform well under specific conditions, applications in general will require enhanced robustness, standardization, and domain adaptability. Addressing these shortcomings opens promising directions for future research in adaptive and intelligent quality monitoring systems.

2.8 Chapter 2 Conclusion

The present chapter has summarized a systematic literature review on the identification of control chart pattern recognition (CCPR) using techniques based on the neural network approach. It has charted the progress of CCPR methods from traditional statistical control charts to current artificial intelligence solutions, describing the improvement brought by deep learning architectures such as Convolutional Neural Networks (CNN), Recurrent

Neural Networks (RNN), and hybrid model in recognizing sophisticated and concurrent patterns in industrial systems.

The review included consideration of primary classifier architectures, assessment metrics, treatment of data methodologies, and outcomes of performance. Bibliometric examination also illustrated increasing global interest and cross-disciplinary contributions to this research theme with increased output of research from nations such as North America and East Asia. Their application in numerous industries, such as manufacturing, automotive, and biomanufacturing, was also mentioned, which showed the extent of utilization and industrial applicability of the models.

Despite these advancements, there exist some important missing links in current research. Many existing studies rely on assumptions such as data normality, stationarity, or class balance, which may not be held in practical industrial contexts, and the fact that there is a lack of standard benchmark sets of data as well as identical evaluation protocols confines fair comparisons of models. Besides, data unbalance, expensive computational needs, low interpretability of models, and the demand for adaptive frameworks that can sense dynamic process regimes are some more challenges.

These limitations highlight the need for CCPR models that are robust, interpretable, and capable of generalization to real-world conditions. On this basis, the subsequent chapter addresses one of the largest gaps in literature by undertaking a comparative assessment of CCPR models in conditions of non-normality. It aims to examine the performance and robustness of various classifiers in scenarios where common assumptions of data distributions no longer hold, while offering further insight into their validity in the real world.

CHAPTER 3

NEURAL NETWORK FOR CONTROL CHART PATTERN RECOGNITION

This chapter Evaluate the performance of neural network models for Control Chart Pattern Recognition (CCPR) under normal as well as non-normal distribution conditions to address the limitation in past research, which is based on assumptions of normality. To provide a better comparison of model capability, various architectures like FNN, CNN, RNN, and hybrid CNN-RNN are compared with synthetic data generated from a number of statistical distributions. Key characteristics are derived to enhance classification, and model performance is assessed using accuracy, sensitivity, specificity, and F1-score metrics. Finally, the models are implemented on industrial-like real-world data to demonstrate their real-world effectiveness in monitoring process variability.

3.1 Control chart Pattern recognition under Non normal distribution

Control chart pattern recognition (CCPR) is a critical aspect of statistical process control (SPC), enabling the detection of abnormal patterns that signify potential process deviations or anomalies. Abnormal patterns such as upward trend (UT), downward trend (DT), upward shift (US), downward shift (DS), and cyclic (CYC) behavior can be attributed to some assignable causes that adversely affect process stability [44]. For example, material, machine or operator change can be detected by shift patterns, while tool wear creates trend pattern. Variance in the voltage supply is witnessed with a cyclic pattern [19]. Different CCPR techniques have been proposed to present an automatic abnormal pattern

classification ([6], [45]; (Zan et al., 2020); [47];[48]). Of these, artificial neural network (ANN) based pattern recognizers are most employed machine learning algorithms for pattern identification and classification of various types of patterns. Traditional approaches to CCPR mostly make normality assumptions on process data; however, real-world manufacturing and service processes generally have non-normal characteristics. Resolving the difficulty of pattern recognition under non-normal situations is an evolving field for study that necessitates the use of advanced neural network approaches.

Accuracy and robustness, along with computational efficiency, have been pursued in various ways using neural networks for CCPR. [43] researched using CNNs with small sample sizes, noting the potential of CNNs in feature extraction and classification. [49] proposed a decision tree hybrid deep learning model to improve the recognition accuracy. (Pacella & Semeraro, 2007) put forward an RNN-based model for the recognition of time-dependent patterns and applied it to temporal dependency learning. [50] emphasized FNNs in the interest of overcoming process variations and improving early detectability. [51] tackled residual-based control charts using convolutional architecture to enhance performance in monitoring.

Other researchers have also worked on various hybrid approaches and ensemble learning methods to enhance the performance of CCPR. [52] explored ensemble methods combining multiple neural architectures to achieve higher accuracy across varying process conditions. [53] studied the impact of noise and process variation on deep learning models and suggested robust preprocessing techniques to enhance model performance. Besides, [13] investigated the performance of transformer-based models on pattern recognition and showed that they were more capable of dealing with complex, high-dimensional data

featuring state-of-the-art performance. Previous works such as [54], [55] and [56] further confirmed that data augmentation and deep feature extraction techniques are essential for model generalization.

Most of the literature focuses on feature engineering and dimensionality reduction to make the models more interpretable and computationally efficient for example [57] proposed a hybrid feature selection framework that combines PCA with concurrent methods for enhancing CCPR accuracy. Meanwhile, [56] explored transfer learning strategies to exploit pre-trained models for rapid deployment in industrial settings. Other studies by [58] ,[59] and [60], applied unsupervised learning methods to detect complex control chart patterns without labeled data.

Most of the existing studies design and evaluate their models assuming normality, which may be a cause of suboptimal performance in real-world applications. It is difficult to tell how much impact is impacted by the skewed distribution, heavy tail, or multimodal, and further investigation will be performed. [15] proposed using the CNN-based multi-feature fusion method to process the imbalanced data of CCPs. This method successfully identified abnormal patterns and obtained a higher classification performance. [61] suggested an autoregressive model combined with a 1D CNN and support vector machine for recognizing control chart patterns in autocorrelated processes, achieving notable accuracy improvements. Most importantly, research by [19], underlined the need for adaptive models that could handle non-normal distributions dynamically.

In this respect, the goal of the current study is to fill this gap in knowledge by studying the relative performance of different neural network models, including CNNs, RNNs, FNNs, and hybrid methods, under non-normality conditions. With several datasets of different

distribution properties, one can compare the robustness, sensitivity, and classification accuracy of the models. The results of this study will add to the accumulated knowledge on the choice of appropriate neural network architecture for efficient CCPR in a non-normal environment.

3.2 Pattern Recognition Techniques for Control Charts

The six primary categories of common control chart patterns are normal, upward shift, downward shift, upward trend, downward trend, and cyclic patterns. Figure 3.1 illustrates these patterns that help diagnose the causes of the systematic variations. Such factors that may cause systematic variations are tool wear, environmental changes, operational errors, or other causes.

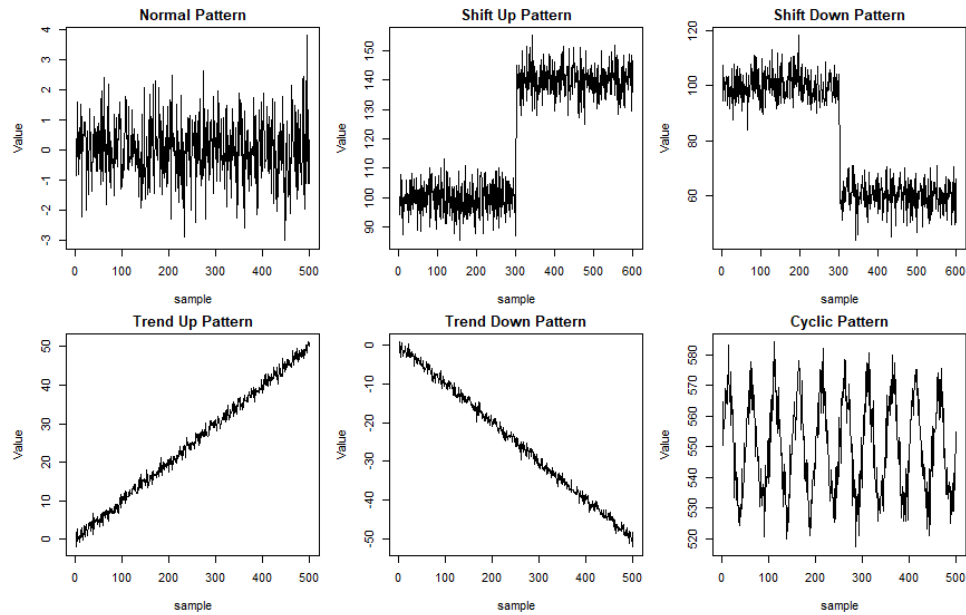


Figure 3.1: Type of Pattern Recognition

(a) Normal Pattern: shows that the process is stable and has only common cause variations. Data points fluctuate randomly around the centerline within the control limits, showing no external disturbances as suggested by [62].

(b) An Upward Shift Pattern; this happens when the process suddenly increases because of factors such as material changes, calibration errors, or operational adjustments. Early detection helps prevent defects as suggested by (R. Guh & Tannock, 1999).

(c) Downward Shift Pattern; shows a sudden drop in the process mean, often caused by machine wear, reduced input quality, or operational inefficiencies. Timely intervention ensures process stability [63].

(d) Upward Trend Pattern; reflects a gradual increase in data points, indicating tool wear, rising temperatures, or systematic deviations. Left unchecked, it can lead to process instability [64].

(e) Downward Trend Pattern; is a steady decline in process values, often due to equipment deterioration or resource depletion. Finding trends early allows predictive maintenance [65].

(f) Cyclic Pattern; displays periodic fluctuations, typically caused by machine cycles, seasonal effects, or operational schedules [65].

The models of references [66], and [67], etc only analyze basic (single) patterns and models of references such as [68], [63], [67], [2], and [69] merely analyze some states of simultaneous occurrence of two pattern.

The late 20th century introduced AI techniques. Early applications of neural networks to CCPR, such as [2], were proposed in the 1990s. New opportunities for pattern recognition improvement were opened by developing statistical learning methods such as SVMs and decision trees. Examples include [70]. Hybrid systems, which combined statistical approaches with AI methods, began to be more prominent in the 2010s and offered better robustness and accuracy.

Table 3.1 presents major parameters related to control chart patterns. These parameters are important for simulating and training recognition models.

Type of pattern	Parameters	Values
Normal	Mean: μ	0
	SD: σ	1
Upper Trend	Gradient: θ	0.075 to 0.1
Down Trend	Gradient: θ	-0.1 to -0.075
Upper Shift	Shift magnitude:	0.7 to 1.5
Down Shift	Shift magnitude	-1.5 to -0.7
Cyclic	Amplitude	0.5 to 1.5
	Period	8

Table 3.1: Parameters for Simulating Control Chart (Sources: Hassan et al, 2006)

3.3 Design of Simulation study

We performed a wide simulation study for the neural network architecture that can handle non-normal conditions. There are six control chart patterns: normal, shift-up, shift-down, trend-up, trend-down, and cyclic. Each pattern was modeled using four different probability distributions, namely normal, gamma, t-distribution, and lognormal. In this simulation, there were 1000 observations for each pattern with 50 subgroups to provide enough statistical variation. We simulate a thousand times across models.

In each run of simulation, 1920 sample patterns were used for training, 600 sample patterns for test evaluation, and 480 sample patterns for in-training validation to allow for early stopping to prevent overfitting. The data was split into 80% training and 20% testing, and another 20% for validation of the training data. Parameters under consideration for

distribution are Gamma: Shape = {4, 8, 16, 32, }, Scale = 1; T-Distribution: df = {4, 5, 8, 10}; Lognormal: Meanlog = 0, Sdlog = 0.2; Normal: Mean = 0, SD = 1.

For this purpose, mean, variance, skewness, kurtosis, cumulative sum, slope, range, and rolling mean features have been drawn based on the statistical and shape-based metrics, respectively. To classify different classes, several models have been considered: FNN_{norm} , FNN_{gamma} , FNN_{tdist} , $FNN_{lognorm}$, CNN_{norm} , CNN_{gamma} , CNN_{tdist} , $CNN_{lognorm}$, RNN_{norm} , RNN_{gamma} , RNN_{tdist} , $RNN_{lognorm}$, and *hybrid CNN – RNN_{norm}*, *hybrid CNN – RNN_{gamma}*, *hybrid CNN – RNN_{tdist}*, *hybrid CNN – RNN_{lognorm}* trained by the Adam optimizer in sparse categorical cross-entropy loss with early stopping to achieve the best learning. Further, these models have been assessed based on their accuracy, precision sensitivity, specificity, and F1-score so that their overall performance concerning the non-normality of data distribution can be investigated.

Figure 3.2 illustrates the basic structure of a feedforward neural network (FNN), comprising an input layer, multiple hidden layers, and an output layer. The hidden layers utilize the Rectified Linear Unit (ReLU) activation function to introduce non-linearity.

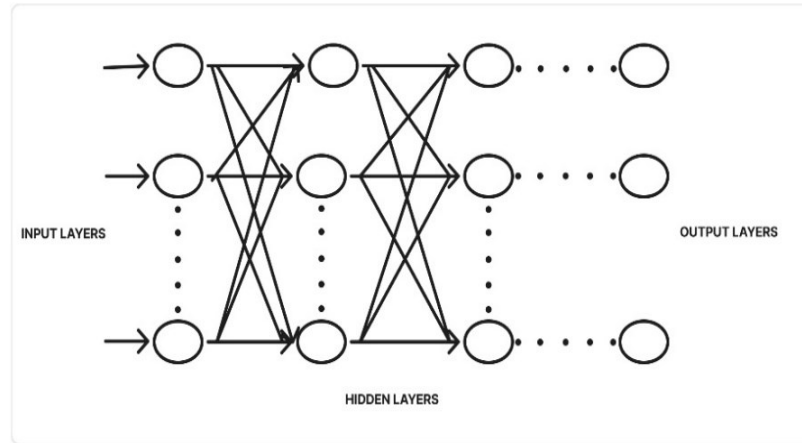


Figure 3.2: Neural Network Architecture

The following Figure 3.3 presents the architecture of the CNN model used in this study, including convolutional and pooling layers followed by fully connected layers. The convolutional layers are responsible for extracting localized spatial features from the input patterns, which are then processed by dense layers to classify the control chart patterns effectively.

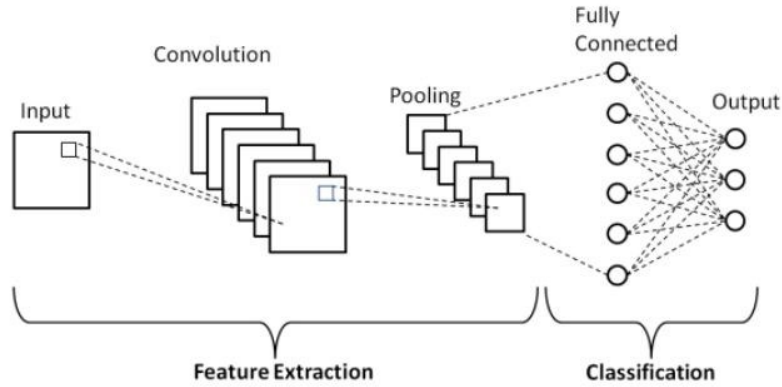


Figure 3.3: CNN Architecture (Priya, V, 2024)

For the output layer will consist of 6 neurons, each representing one of the six CCPR categories (random, shift up, shift down, trend increase, trend decrease, and cyclic). The SoftMax activation function will be used for multi-class classification:

$$\sigma(z)_j = \frac{e^{z_j}}{\sum_{k=1}^K e^{z_k}}$$

where $K = 6$ is the number of classes.

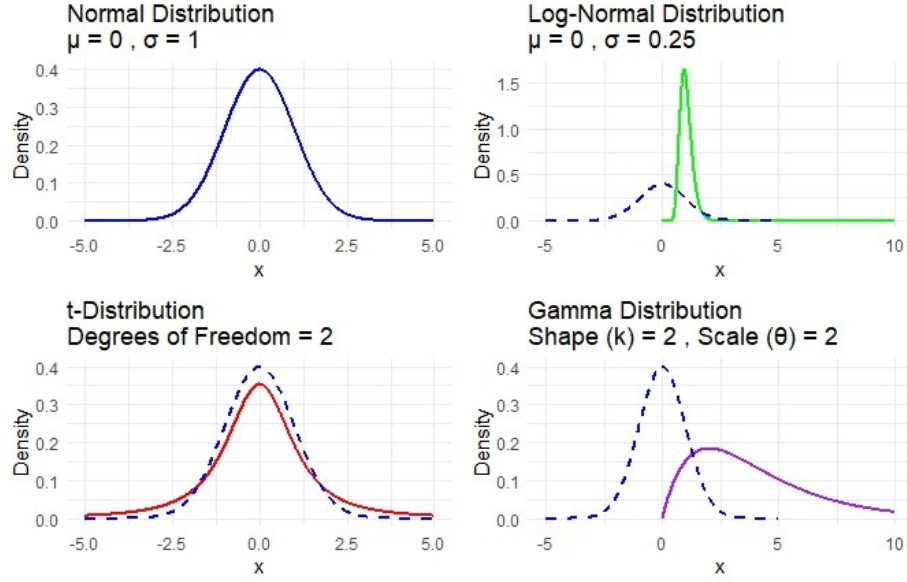


Figure 3.4: Density of Distributions

Feature extraction involves deriving meaningful metrics from the data to aid in pattern recognition. The extracted features can be categorized into statistical and shape features. The extracted features can be categorized into statistical and shape features (Smith et al., 2020; Chen et al., 2023; Patel et al., 2023). Similarly, some studies used to optimize and select the important features, Hassan et al., (2006). To ensure consistency and improve model training performance, normalization techniques are also applied to scale the extracted features within a standardized range.

Features	Type	Formula
Mean	Statistical	$\mu = \frac{1}{N} \sum_{i=1}^N x_i$
Variance		$\sigma^2 = \frac{1}{N} \sum_{i=1}^N (x_i - \mu)^2$
Skewness		$SKE = \frac{\frac{1}{N} \sum_{i=1}^N (x_i - \mu)^3}{\left(\frac{1}{N} \sum_{i=1}^N (x_i - \mu)^2 \right)^{\frac{3}{2}}}$

Kurtosis		$Kurt = \frac{\frac{1}{N} \sum_{i=1}^N (x_i - \mu)^4}{\left(\frac{1}{N} \sum_{i=1}^N (x_i - \mu)^2 \right)^2}$
Slope	Shape	$\beta_0 = \frac{N \sum x_i y_i - \sum x_i \sum y_i}{N \sum x_i^2 - (\sum x_i)^2}$
Range		$Range = \max(x) - \min(x)$
Cusum		$CUS_i = \sum_{j=1}^i (x_j - \mu)$
Rolling mean		$Rm_t = \frac{1}{k} \sum_{i=t-k+1}^t x_i$

Table 3.2: Features Extraction

3.4 Results for simulations

The Feedforward Neural Network (FNN) model, introduced in Chapter (2), is evaluated first for its performance across different distribution types. For Figure 3.5 the FNN_{norm} model achieved outstanding performance under the normal distribution assumption, with a mean accuracy of 99.2%. Sensitivity and specificity are also very high across patterns, suggesting excellent detection and true negative identification. The precision rate is over 95 %, with an F1-score of 97%, indicating a well-balanced model in terms of precision and recall.

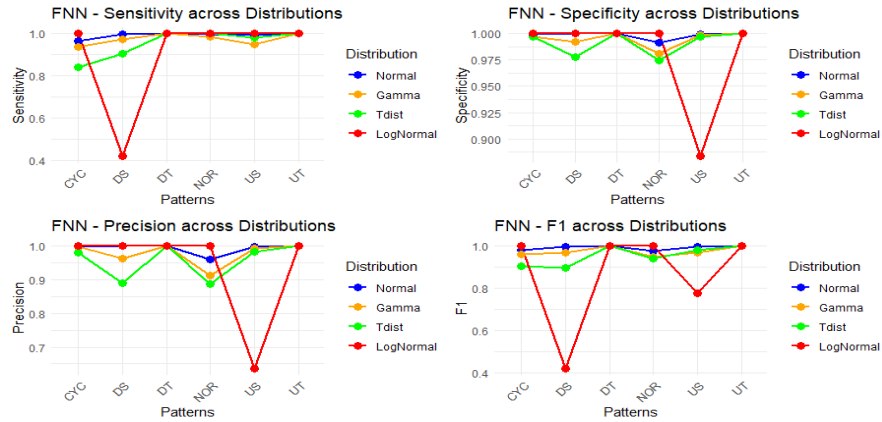


Figure 3.5: FNN across Distributions

The FNN_{gamma} model has the best overall results among all gamma distribution shapes. The findings demonstrate that small shapes had the highest accuracy, which remained steady at 97.38%, with sensitivity values ranging from 94.66% to 100% and specificity consistently over 98%. The FNN_{gamma} model had good precision and F1n-scores, touching 1.000 in several instances, showing that it was capable of spotting non-normal control chart patterns.

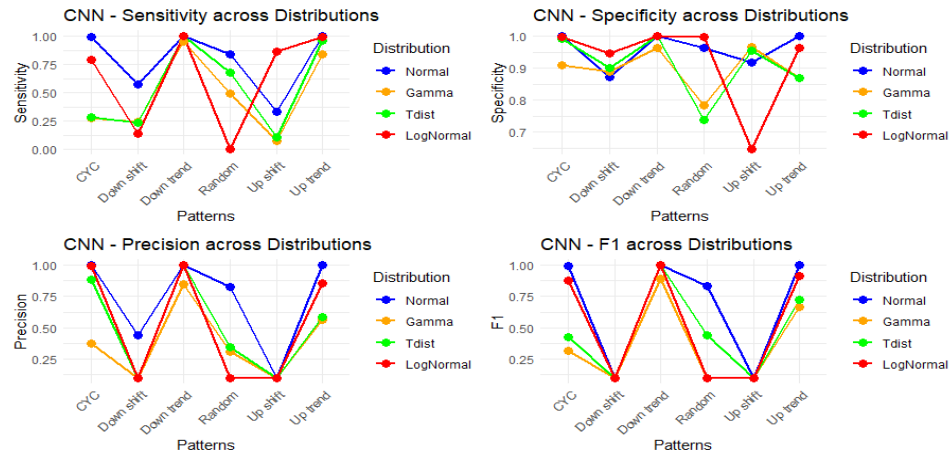


Figure 3.6: CNN across Distribution

Next, the Convolutional Neural Network (CNN) model is assessed for its pattern recognition capabilities across varying data distributions. Figure 3.6 illustrates the performance of the CNN_{norm} model across four statistical distributions, the results indicate that Up Trend and Down Trend consistently achieve high scores across all metrics (Sensitivity, Specificity, Precision, and F1-score), making them the most reliably classified patterns. In contrast, Random, Up Shift, and Down Shift exhibit lower sensitivity and precision, particularly under Gamma and T-distributions, indicating increased classification difficulty.

Among the distributions, the Normal distribution provides stable performance across all metrics, while Gamma and T-distributions result in lower sensitivity and precision in certain patterns. The Log-normal distribution demonstrates high variability, excelling in some cases but causing performance drops in others.

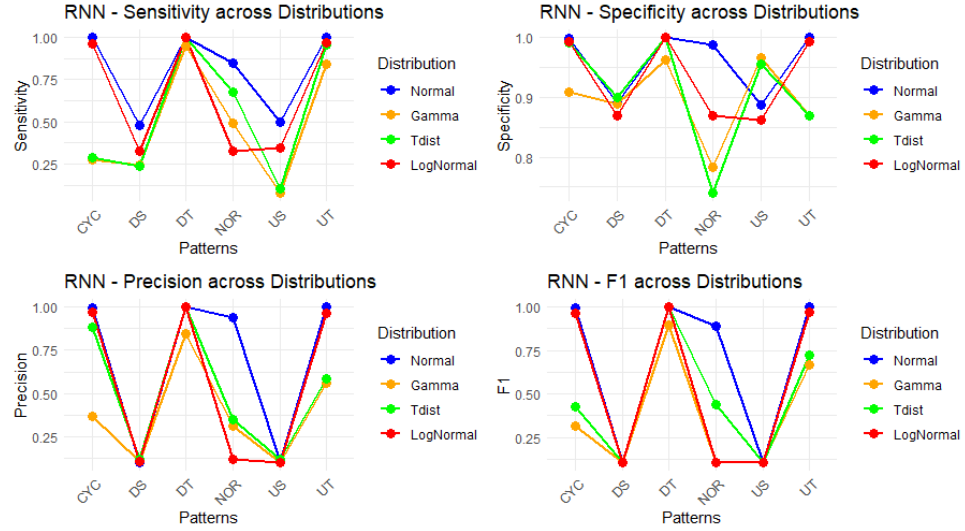


Figure 3.7: RNN across Distributions

The Recurrent Neural Network (RNN) model, which is well-suited for temporal data, is evaluated next. Figure 3.7 evaluates the RNN model's performance, up and down trend patterns consistently achieve high sensitivity, precision, and F1-scores, indicating reliable classification. In contrast, US and DS patterns perform poorly, especially under Gamma and T-distributions, where sensitivity and precision drop significantly.

Normal distribution provides stable results, while Gamma and T-distributions lead to lower performance across multiple metrics. The Log-normal distribution shows variability, with fluctuating results depending on the pattern.

Overall, the RNN model excels at structured trends (Up Trend, Down Trend) but struggles with US and DS patterns, particularly under non-Normal distributions.

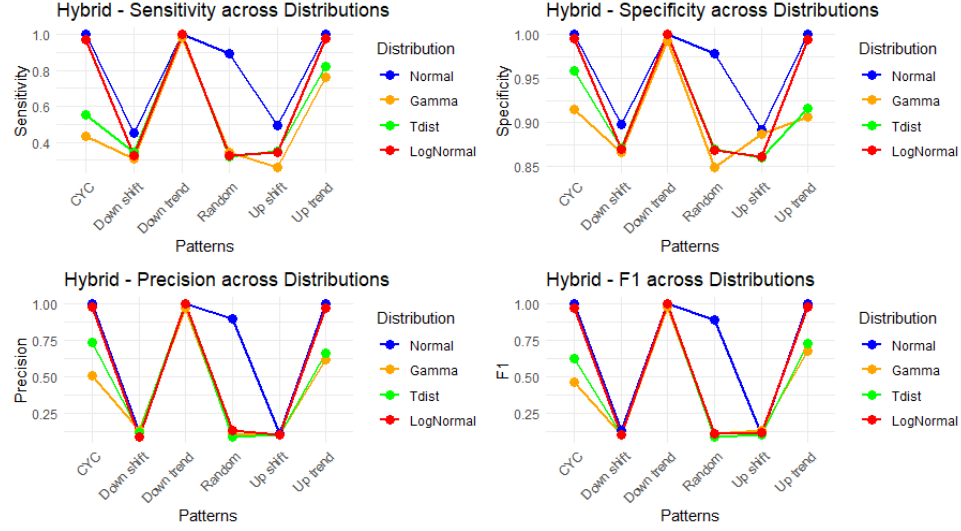


Figure 3.8: Hybrid CNN-RNN across Distributions

Finally, the hybrid CNN-RNN model, combining the strengths of spatial and sequential learning, is tested under different distributions. Figure 3.8 evaluates the hybrid CNN-RNN model. The model performs exceptionally well for Up Trend and Down Trend patterns, achieving consistently high sensitivity, specificity, precision, and F1-scores across all distributions.

However, Random, Up Shift, and Down Shift patterns struggle, particularly under Gamma and T-distributions, where sensitivity and precision drop significantly. The Normal distribution provides the most stable performance, while Gamma and T-distributions exhibit noticeable variability. The Log-normal distribution performs well in some cases but shows fluctuations across patterns.

Overall, the Hybrid CNN-RNN model demonstrates strong performance in structured patterns (Up Trend, Down Trend), but its effectiveness decreases for Random, Up Shift, and Down Shift patterns, particularly in non-Normal distributions.

3.5 Performance Comparison for Models

Four neural network models FNN, CNN, RNN, and Hybrid CNN-RNN are compared based on accuracy and adaptability for varying data distributions. Model performance is highly dependent on data features, particularly in non-normal situations, which affect classification accuracy and sensitivity.

Some architectures are robust for a range of distributions, while others fail significantly, especially with shifts and cyclic fluctuations. These results bring into focus the importance of choosing an appropriate model for the neural network for CCPR, both based on data features and requirements of detection.

Models/Distributions	Normal	Gamm (4,2)	T (8)	T (10)	Lognormal
FNN	99.2%	97.38%	92.29%	95.41%	90.285
CNN	80.53%	38.65%	54.64%	56.77%	65.41%
RNN	79.1%	36.65%	54.64%	56.77%	62.48%
Hybrid CNN-RNN	80.60%	47.51%	56.21%	56.39%	65.68%

Table 3.3: Comparison of Accuracy

As shows Table 3.3, FNN performs best of all other models, with 99.2% accuracy under regular conditions. It has high classification reliability for gamma, t-distribution, and lognormal data sets and is best suited to identify various control chart patterns with less sensitivity to statistical shifts.

The Hybrid CNN-RNN model is a close second, performing well in cyclic pattern recognition. With CNN's spatial feature extraction and RNN's sequential learning

combined, it detects periodic fluctuations well, albeit at a slightly lower overall accuracy compared to FNN.

CNN and RNN models demonstrate tremendous shortcomings under non-normal distributions. CNN performs poorly with sequential dependency, resulting in poor identification of trend and shift patterns. Its accuracy reduces from 80.53% when normally distributed to 38.65% under the gamma distribution.

RNN, which is optimized for sequential learning, performs erratically over distributions, especially for sudden shifts. Its accuracy reduces in the same manner as CNN, and hence it becomes less dependable in real-world industrial processes with lots of process fluctuations.

3.5.1 Impact of Data Distribution on Model Performance

Data distribution has a considerable impact on the model's performance. For normal distributions, FNN performs almost perfectly with classification rates, and CNN and RNN perform reasonably well. For gamma, t-distribution, and lognormal data sets, the CNN and RNN models are severely impacted in terms of accuracy loss.

These models are poor with skewness and heavy tails, which are common in real manufacturing data. Under gamma and t-distributions, their accuracy is less than 40%, demonstrating extremely poor generalization in complex, non-normal situations.

FNN remains extremely robust, with over 90% accuracy for all distributions. This suggests that feedforward architectures are less vulnerable to deviations from normality, thus are more reliable under uncertain data distribution.

Another critical characteristic of lognormal distribution that worsens the misclassification error is its extreme right-skewness. Irregular behavior from the CNN and RNN models signifies the fact that they struggle to determine the shift patterns of skewed distributions.

3.6 Application for Control Chart Pattern Recognition

Practical application of Effective Control Chart Pattern Recognition (CCPR) in industrial settings requires models that are computationally effective, sensitive to non-normal distributions, and precise in detecting process variations. Selection of the neural network model is critical because different models perform differently depending on data characteristics [19].

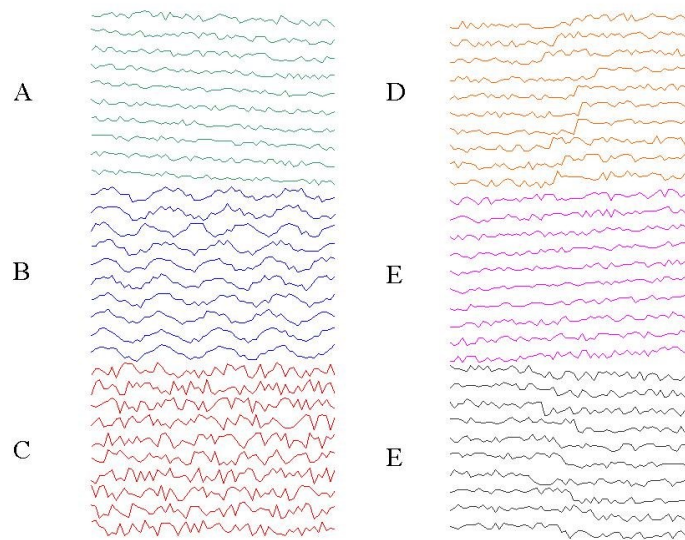


Figure 3.9: Class of Control Chart

This study employs the Synthetic Control Chart Time Series data from the UC Irvine Machine Learning Repository [71]. Very commonly applied in CCPR studies [72]. As the above figure 3.9 shows, the dataset offers an organized standard for model assessment. It univariates contains six control chart pattern types: normal (C) (1-100), upward shift (D) (101-200), downward shift (F) (201-300), upward trend (E) (301-400), downward trend

(A) (400-500), and cycle (B) (501-600). Such systematic data allows systematic feature extraction and stable model training.

Assumption	Test	p-value / Statistic
Normality	Anderson-Darling Test	$p < 6.867e-10$
Homoscedasticity (Equal Variance)	Bartlett's Test	$p < 2.2e-16$
Independence (Autocorrelation)	Durbin-Watson Test	DW = 0.6015, $p < 2.2e-16$

Table 3.4: Summary of Assumption Testing Results

The results of the Table 3.4 indicate that the data is not normally distributed, as confirmed by the Anderson-Darling test. Bartlett's test indicates unequal variances across groups, which is an indication of heteroscedasticity. Furthermore, the Durbin-Watson test confirms strong positive autocorrelation, i.e., dependence of observations over time. All these results call for the application of robust modeling techniques that can account for non-normality, variance instability, and autocorrelation.

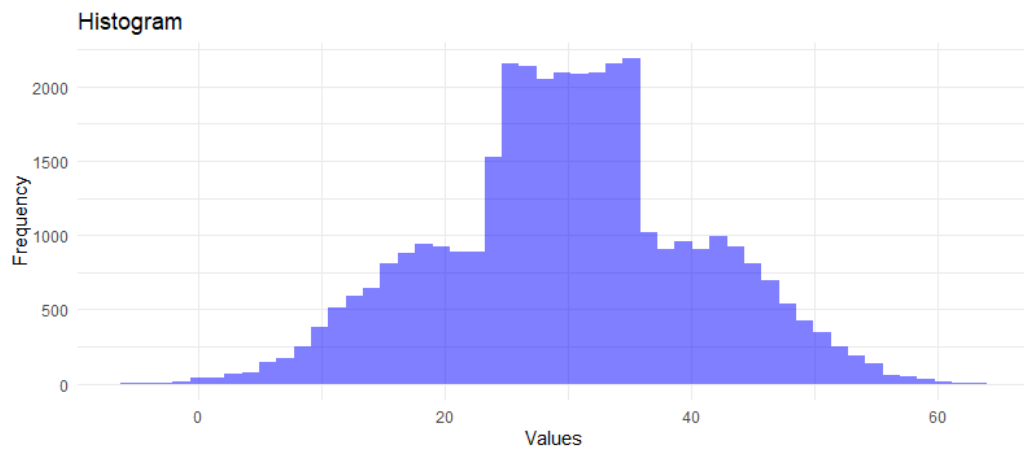


Figure 3.10: Histogram of Synthetic Control Data

The Above Figure 3.10 is tested frequency distribution of values in the data set. The fact that there are two high points suggests a bimodal instead of normal bell-shaped curve distribution. This agrees with the outcome of the normality tests, which is that the data set is not Gaussian distributed.

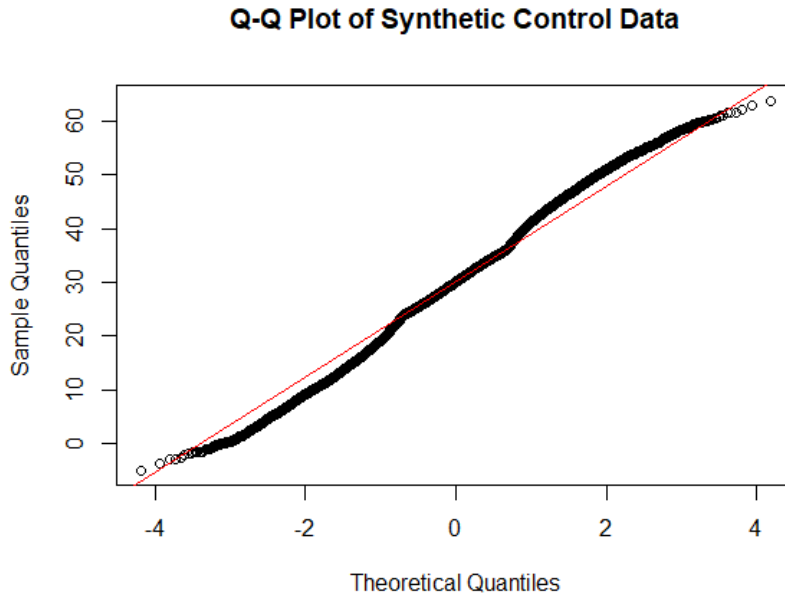


Figure 3.11: Q-Q Plot of Synthetic Control Data

The Q-Q plot for Figure 3.11 also provides additional evidence of non-normality. Skewness and heavy-tailedness are evidenced by deviations from the theoretical normal line, especially at the tails. This suggests that parametric models under the assumption of normality may not be appropriate for this data.

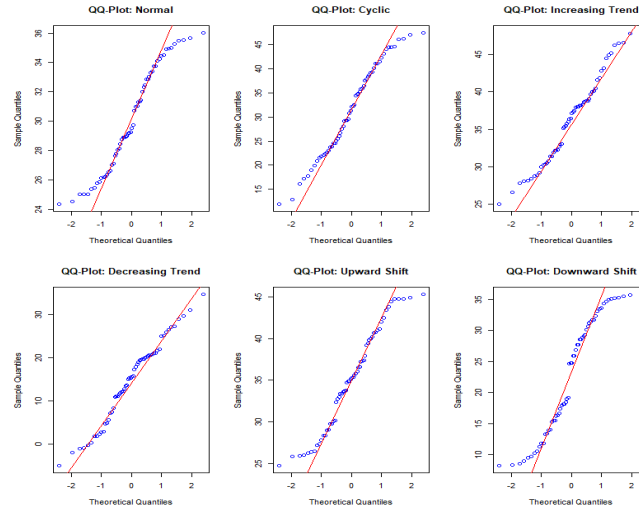


Figure 3.12: Q-Q Plots for Different Control Chart Patterns

Q-Q plots for Figure 3.12 of other control chart patterns also indicate deviations from normality across different categories. Some patterns reflect higher deviations from the normal line, indicating different features of distributions for different process conditions. This underlines the necessity to use models that can work well under non-normal distributions.

3.6.1 Model Performance in Industrial Settings

Table 3.5 shows the accuracy and confidence intervals in different neural network models. FNN is the most accurate with accuracy at 95.00% and a confidence interval of (0.8943, 0.9814) and is the most consistent and stable model for different data distributions. Its lack of use of sequential dependencies in generalization makes it most suitable for CCPR applications [50].

Models	Accuracy of recognition	95% of C. I
FNN	0.9500(0.9115)	(0.8943, 0.9814)
CNN	0.9083(0.9111)	(0.8419, 0.9533)
RNN	0.8166(0.8073)	(0.7357, 0.8814)
Hybrid cnn-rnn	0.9333(0.974)	(0.8729, 0.9708)

Table 3.5: Accuracy and confidence of interval (training accuracy)

The Hybrid CNN-RNN model is closely matched with 93.33% accuracy and confidence interval (0.8729, 0.9708). The model benefits from the feature extraction capabilities of CNN and the sequential learning capacity of RNN, hence particularly well suited to detect cyclic patterns. Utilization of convolutional and recurrent layers allows the model to manage localized and sequential features and hence improve classification performance in complex industrial settings.

CNN and RNN models individually possess a slightly lower accuracy of 90.83% with confidence intervals (0.8419, 0.9533). While CNN is unable to identify sequential trends, RNN is incapable of distinguishing localized spatial features [43]. Such models, though strong, are even stronger when combined into a hybrid framework that compensates for their flaws when operating separately.

3.6.2 Confusion Matrix

Confusion matrices also indicate classification strengths and weaknesses across the models. FNN has minimal misclassification, whereby most of its errors are between Downward Shift (DS) and Upward Shift (US). Hybrid CNN-RNN model, in general, accurate, is confused between Downward Trend (DT) and Downward Shift (DS), which

implies challenges in distinguishing among gradual versus abrupt changes in process behavior.

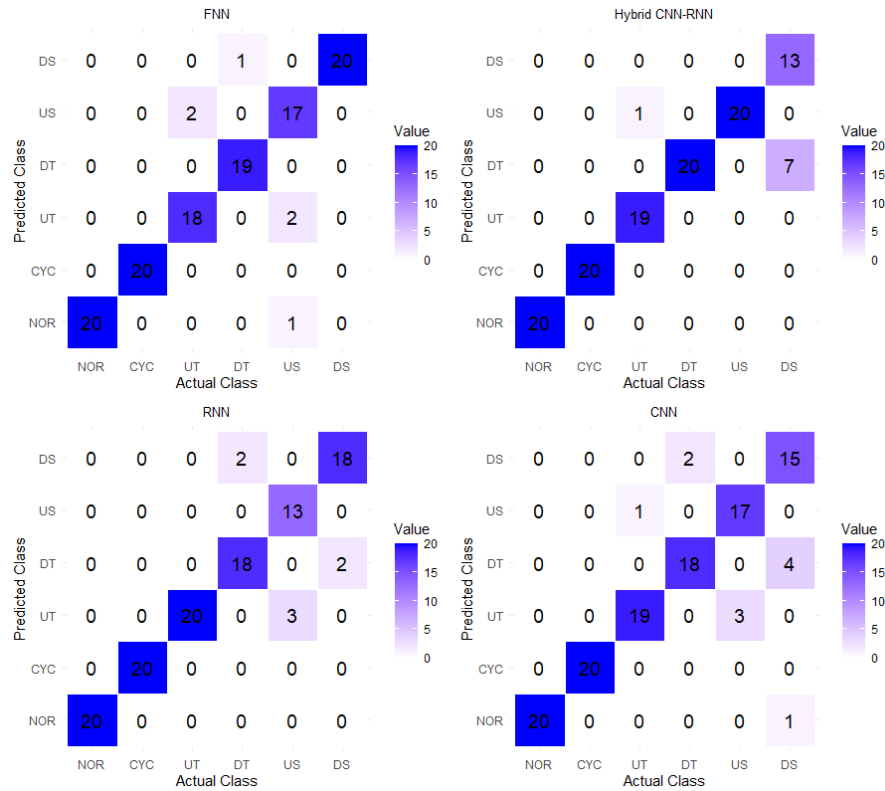


Figure 3.13: Heatmap of Confusion Matrices

There are more frequent misclassifications with CNN and RNN models. It is challenging for CNN to classify Upward Trend (UT) and Downward Trend (DT) because CNN emphasizes spatial features. RNN, on the other hand, mistakenly classifies Upward Shift (US) and Downward Shift (DS) as evidence of its weak capacity for spatial dependency learning. All these points towards the strength of hybrid models possessing both feature extraction and sequential processing capabilities.

In practice, these findings mean that FNN is the best for stable and high-precision CCPR implementation, particularly when general classification performance is on the priority list. However, where cyclic and sequential relationships are of top concern, the Hybrid CNN-

RNN model is the better compromise. The used dataset closely resembles the conditions of real-world manufacturing processes and hence serves as a suitable benchmark for testing model performance in industrial settings.

3.7 Chapter 3 Conclusion

In this chapter, we investigate the performance of different neural network model architectures, including FNN_{norm} , FNN_{gamma} , FNN_{tdist} , $FNN_{lognorm}$, CNN_{norm} , CNN_{gamma} , CNN_{tdist} , $CNN_{lognorm}$, RNN_{norm} , RNN_{gamma} , RNN_{tdist} , $RNN_{lognorm}$, and *hybrid CNN – RNN_{norm}*, *hybrid CNN – RNN_{gamma}*, *hybrid CNN – RNN_{tdist}*, *hybrid CNN – RNN_{lognorm}* for CCPR problems in non-normal conditions. Considering that real industrial data often does not meet normality assumption, the study considered different distributions such as normal, gamma, T-distribution, and lognormal for generating data that closely mimics practical applications of industrial situations.

Our results showed FNN_{norm} , FNN_{gamma} , FNN_{tdist} , $FNN_{lognorm}$ had the maximum accuracy, sensitivity, and specificity in all the models and under all distributions, indicating its robustness to changes in features of distribution. This is an indication that the model is feasible for real-world applications under a non-normal process variation. The *hybrid CNN – RNN_{norm}*, *hybrid CNN – RNN_{gamma}*, *hybrid CNN – RNN_{tdist}*, *hybrid CNN – RNN_{lognorm}* models also had a good performance, specifically on precision and recall, which might be adequate for solving complex pattern recognition problems.

In other hand, CNN_{norm} , CNN_{gamma} , CNN_{tdist} , $CNN_{lognorm}$, and RNN_{norm} , RNN_{gamma} , RNN_{tdist} , $RNN_{lognorm}$ models performed more moderately to poorly, especially when it came to the detection of shift and cyclic patterns under conditions of non-normal

distributions. This vividly highlights the weakness in sequential and spatial pattern learning while capturing the subtlety of complex process fluctuations. This perhaps indicates that optimization and feature engineering for those models need further work when put under conditions that are not normal.

These results once again hint at the importance of selecting appropriate neural network architectures regarding the distribution underlying the data. In real-world model selection applications, skew, kurtosis, and other distribution properties should be considered to improve CCPR performance. Further research needs to be done to develop hybrid approaches which better integrate domain knowledge with the state-of-the-art deep learning methods including attention mechanisms and transformer models for improved detection accuracy and robustness.

CHAPTER 4

INTEGRATION MCUSUM CONTROL CHART AND NEURAL NETWORK FOR DETECT ABNORMAL SHIFTS PROCESSES

This chapter is a comparison of the performance of the $MCUSUM_{nn}$ monitoring scheme suggested here in varying process settings, for example, different shift types and distributional contexts. Unlike the traditional approach focused on standard assumptions, our approach compares both symmetric and asymmetric distributions to have a robust and representative data analysis of data in existence. For practical use, the chapter compares the detection power of the $MCUSUM_{nn}$ chart with the control chart benchmark T^2_{nn} . An exhaustive simulation study is conducted to identify the performance of every chart in identifying changes with varying magnitudes. Finally, the chapter presents extensive performance results through tabular summaries and graphical plots and reveals circumstances where $MCUSUM_{nn}$ outperforms standard models.

4.1 Introduction

4.1.1 Statistical Process Control and Multivariate Charts

Statistical Process Control (SPC) is a fundamental quality management methodology that provides tools to observe a process in real time and catch abnormalities early. Walter A. Shewhart initially formulated SPC in the 1920s, and he began with the univariate control charts $\bar{X}$ and R, which are still widely used to monitor single quality characteristics.

However, modern industrial processes increasingly involve several dependent variables. The variables have complex relationships and monitoring each separately with univariate charts may not detect multivariate shifts or lead to misleading conclusions. It was this

difficulty that induced the evolution of Multivariate Statistical Process Control (MSPC) which takes into consideration the covariance structure of quality characteristics and enables monitoring of more than one variable at the same time.

Hotelling's T^2 statistic formed the mathematical foundation for multivariate control charts, scientists had developed MEWMA and MCUSUM charts to improve performance in detecting smaller shifts.

The problem of diagnosis., identifying which specific variable(s) are the cause when a chart suggests an out-of-control condition was highlighted by Mason, [73]. In response, [74] proposed the d value decomposition which calculates each variable's contribution to the T^2 statistic by removing variables one at a time and then re-calculating the statistic. This was widely referenced for its simplicity of use and simplicity of interpretation.

Despite such advances, classical MSPC charts still rely on strong assumptions of multivariate normality, linearity, and independence. These are often violated in industrial applications, and thus researchers have looked for adaptive and model-based methodologies that can be executed under more assumptions.

4.1.2 Types of Multivariate Control Charts

Hotelling's T^2 chart was first developed by [75] as a multivariate extension of the univariate $\bar{X}$ chart. It has since then become a staple tool in multivariate quality control. Lowry et al. (1992) proposed MEWMA for better detection of small shifts by assigning exponentially decreasing weights to the newer data. It works well when inspecting slow, continuous shifts in the process mean.

Multivariate Cumulative Sum charts were originally introduced by [76] and were later generalized by [77]. Similar to its univariate version, MCUSUM is designed to detect small continuous shifts in the mean vector. It is very useful in such processes where an early detection of high necessity exists.

Each chart has been developed to address individual circumstances. T^2 charts perform well in ideal conditions but are not satisfactory in noisy or autocorrelated situations. MEWMA and MCUSUM small, better fault detection sensitivity.

4.1.3 Recent Studies and Applications

To counter the limit of traditional control charts, the integration of Artificial Neural Networks (ANNs) into SPC models has been increasingly prevalent. Neural networks possess the ability to model complex, nonlinear relationships and are distribution-free in nature and hence well suited to today's manufacturing environments characterized by noisy or non-normal data.

One of the earliest applications of ANN integration into SPC was presented by [78], who proposed a two-stage ANN for fault detection and classification in multi-attribute control scenarios. Their methodology was superior to traditional multivariate T^2 charts, particularly when there were small samples.

[79] suggested implementing a Self-Organizing Map (SOM)-based and Minimum Quantization Error (MQE) chart monitoring system that eliminates statistical distributional assumption dependence. Their MQE-based system had exhibited stability against non-normality and autocorrelation with a visualization-based and numerical approach to detecting outliers.

[80] made a useful contribution by integrating Hotelling's T^2 , RAM decomposition, and backpropagation neural network. Their method employed d-values and unprocessed variable data as inputs and learned to identify the out-of-control variables more effectively than RAM alone. The hybrid method was shown to possess high potential for scalable, interpretable diagnostics.

Recent studies have pushed the envelope for hybrid MSPC systems. [81] presented a system that combines Multivariate control charts and a multilayer perceptron (MLP), with great fault detection within a printed circuit board (PCB) production setting. This is a move in the direction of fully integrated detection-diagnosis systems. Some of the notable contributions include like [82] Proposed a decision-tree learning model better than traditional ANNs in terms of learning speed and fault apportionment for bivariate processes. [83] Applied auto-associative neural networks to wind turbine data, separating multiple faulty features through residual analysis. [31] Proposed a compositional data pattern recognition model through MLFFNN and isometric log-ratio transformations for minute shifts and trends identification.

[84] proposed robust nonlinear PCA with adaptive bottleneck networks to cope with non-Gaussian distributions and improve early fault detection. [74]; [73] provided valuable methodologies for decomposition and diagnostics within the MSPC framework.

While the integration of neural networks with SPC has been very promising, most of the existing literature focuses on T^2 -based models, typically assumes normality, and rarely employs memory charts like MCUSUM in their frameworks. Moreover, a few systems can handle multi-label outputs, attribution variables, and shift-type classification at the same time.

4.2 Multivariate Control Charts and Neural Network Combination

The evolution of multivariate control charts has greatly enhanced the detection of process shifts early, particularly in intricate industrial processes. Yet, a drawback remains while charts such as Hotelling's T^2 , MEWMA, and MCUSUM can signal an out-of-control condition, they do not identify which variable(s) triggered the shift, nor do they convey information regarding the type of shift itself (e.g., trend, cyclic, abrupt). In a bid to bridge this diagnostic deficit, researchers have turned to artificial neural networks (ANNs), a type of machine learning algorithm that is capable of learning complex patterns from data.

There are several advantages that neural networks present when used in Statistical Process Control (SPC). They are, for starters, distribution-free, meaning they do not require the assumption of multivariate normality, which most standard control charts have to rely on. They are also able to handle nonlinear relations and high-order variable interactions. They are able to, if suitably trained, surpass mere classification of the occurrence and be able to point out the source of the fault as well as, possibly, the type.

[80] presents to link ANNs and SPC frames. They integrated the use of a backpropagation neural network with Hotelling's T^2 chart. In their system, both raw input variables and d -values from the RAM were utilized as inputs for the neural network. Network output was designed to indicate which variable(s) are out-of-control. By training the model on a few fault patterns, the ANN could potentially perform better than RAM in fault variable selection in cases of multiple or minor changes.

Similarly, [85] used a two-layer ANN that was capable of monitoring multiple types of nonconformities (e.g., counts or proportions) of a product. Instead of employing multiple

np or c charts, they developed a single network which could detect and classifying changes in multiple attributes. Their approach had less false alarm rates and better classification accuracy than multivariate and single univariate charts.

Other studies also studied the changes to the T^2 -ANN structure. For example, [79] created a DPSO-optimized selective neural network ensemble for bivariate process monitoring. Their ensemble approach increased robustness and generalization and reduced false negatives and optimized average run length (ARL) for small shifts.

While Hotelling's T^2 was the starting point, other multivariate control charts have now been hybridized with neural models: [86] hybridized MEWMA charts using a neural network to approximate the change-point and contributory variables. Their method showed improved fault localization of dynamic processes.

[81] developed a robust hybrid system multivariate control charts with a multilayer perceptron neural network in identifying out-of-control situations in a printed circuit board (PCB) process. [87] introduced a residual control chart using a neural network for autocorrelated multivariate data. To enhance interpretability, they employed Layer-wise Relevance Propagation (LRP) to determine the responsible variable(s), showing the promise of explainable AI in SPC.

Other researchers have incorporated pure neural architectures into multivariate control systems using ensemble learning [31], fuzzy classification [88], and graph-theoretic visualization [89], among others.

4.3 Proposed Integration of MCUSUM and Neural Networks

4.3.1 Hotelling's T^2 and MCUSUM control chart

Hotelling's T^2 statistics are a classical method used to monitor the mean vector of multivariate processes. It is suitable for detecting large changes and the T^2 statistic is a multivariate counterpart of the univariate Shewhart chart and is given by:

$$T^2 = (\bar{x} - \mu)^T \Sigma^{-1} (\bar{x} - \mu) \quad (4.1)$$

Where $\bar{x}$ is the sample mean vector, μ is the in-control process mean vector and Σ is the variance-covariance matrix of the process.

The control limit for the T^2 chart is given by:

$$UCL = \frac{p(m+1)(n-1)}{mn-m-p+1} F_{\alpha, p, nm-m-p+1} \quad (4.2)$$

Where p is the number of variables, n is the sample size and m initial samples for the quality attributes. Although helpful in large shifts, the T^2 chart is not as sensitive for small and moderate shifts in the process mean vector. For improved detection ability, particularly for smaller shifts.

To increase the sensitivity of detection for small to moderate changes, [76] proposed the MCUSUM chart. Smaller shifts are easily detected by memory type control charts [90]. The method recursively updates a cumulative sum vector S_i , whose statistics are calculated as:

$$C_i = \{(S_{i-1} + X_i)^T \Sigma^{-1} (S_{i-1} + X_i)\}^{1/2} \quad (4.3)$$

With

$$S_i = \begin{cases} (S_{i-1} + X_i) \left(1 - \frac{k}{c_i}\right), & \text{if } C_i > k \\ 0, & \text{Otherwise} \end{cases} \quad \text{for } i=1,2, \dots \text{ and } S_0 = 0$$

Where, $k>0$ is a reference value (our case 0.5). Σ is the covariance matrix, and X_i is the observation vector.

$$C_i = \{S_i^T \Sigma^{-1} S_i\}^{1/2} \quad (4.4)$$

Then the process is out of control if, $C_i > h$. where h is control limit.

4.3.2 RAM Method for Contribution of Variables

To find the variables producing an out-of-control signal, the Runger, Alta and Montgomery (RAM) that was constructed by [74] is used.

Let the first MCUSUM test statistic be T^2 and let T_j^2 be the test statistic whose j_{th} variable is deleted. Then the RAM contribution, termed as the d-value, of the j_{th} variable is defined as:

$$d_j = T^2 - T_j^2 \quad j=1, 2, \dots, p \quad (4.5)$$

Those variables whose values of d_j are higher are more likely to have led to the out-of-control condition. Furthermore, according to Runger, Alt and Montgomery (RAM), if the value of d_j is greater than $\chi_{\alpha,1}^2$ then the i_{th} variable is out of control.

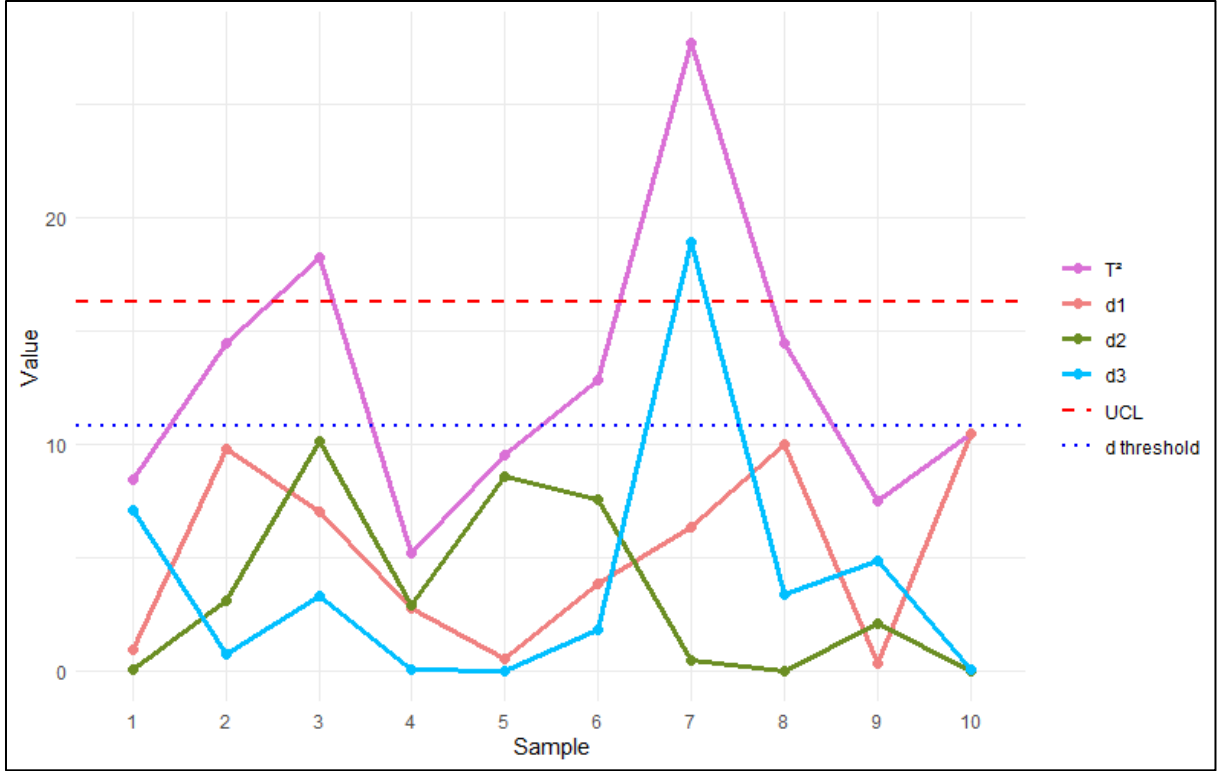


Figure 4.1: The D-value and Hotelling's T^2 Values

Figure 4.1 the d-value and T^2 thresholds were established by applying the χ^2 distribution with $\alpha = 0.001$ significance level. Specifically, the d-value threshold was 10.83, and the UCL of T^2 was 16.27.

4.3.3 Feedforward Neural Network Integration

To complement the detection capability of the MCUSUM chart and enhance fault interpretation, this work includes a Feedforward Neural Network (FNN) as a classification layer. The neural model accepts two significant sources of input for the mean-shifted process vector and d_j vector of RAM-derived contributions. This additional input provides the network with raw process deviation as well as variable-wise diagnostic information.

The architecture of the FNN consists of an input layer of size $2p$, followed by hidden layers with nonlinear activation functions, and a single output neuron with a sigmoid activation

function. The output, $\hat{y}_t$ is the probability that the process is out-of-control at time t . During training, the network minimizes the binary cross-entropy loss function according to supervised labels $y_t \in \{0,1\}$ in which an in-control state is denoted by 0 and an out-of-control state is denoted by 1. During this training, the model learns from experience how variable shifts and RAM contribute to different combinations map to faulty states. Following training, the FNN is a rapid and adaptive classifier: when the MCUSUM statistic T_t^2 passes its control limit H , the model classifies the corresponding u_t vector as to whether the signal is indeed the result of a fault or not.

The integration of this with traditional control charting complements the latter's ability by furnishing not only signal detection, but also state-of-process classification based on multivariate, distribution-adaptive input features. The result is an early detection and explainable diagnosis hybrid system, which is adaptable to various process distributions and operation conditions. As shown in Figure 4.2, this structure allows each input node, which represents a raw deviation or contribution from RAM, to contribute to the classification outcome by the network's learned weights. This allows for detection not just of the occurrence of a change, but also of the relative contribution of each variable, enhancing interpretability of the diagnostic result.

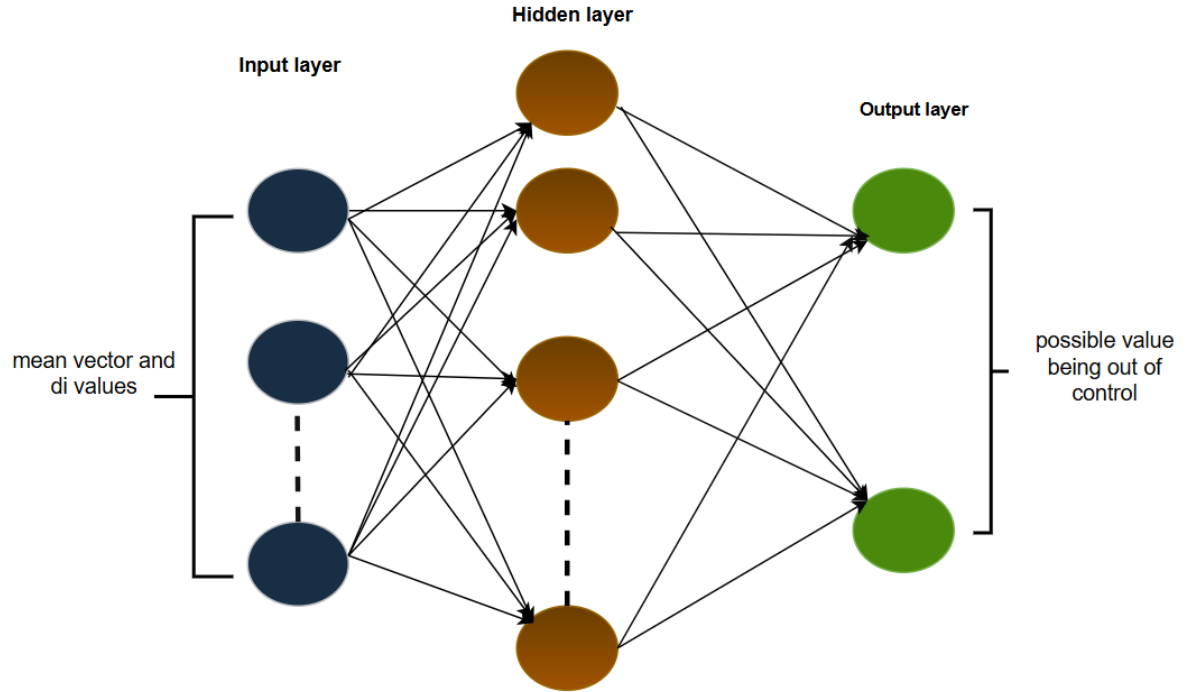


Figure 4.2: Architecture of the Proposal FFNN for Process Classification

4.4 Design of simulation

To quantify the performance of the proposed MCUSUM-FNN integration, an experiment design using simulations was established. The design aims to measure the system's ability to detect and signal process shifts under various statistical distributions and shift patterns and to compare its accuracy with a less conventional model merging Hotelling's T^2 chart and a feedforward neural network T^2_{nn} . The experiments were conducted using the R programming language, employing Monte Carlo simulations to ensure robustness and statistical consistency across repeated trials.

The simulation process has three quality characteristics ($p=3$) having a multivariate distribution when in control. Each measurement is the average of five subgroup measurements ($n=5$), which is typical SPC practice of several measurements being

aggregated into rational subgroups. For each scenario, 100 observations in control were employed to establish the phase 1 baseline from which the process mean vector μ_0 and covariance matrix Σ_0 were determined. This initial information was subsequently used to fine-tune the parameters of Hotelling's T^2 chart and Crosier's MCUSUM chart. Specifically, control limit for T^2 was established using F-distribution at 0.001 significance level, and MCUSUM was established with reference parameter $k=0.5$ and decision limit $h=6.88$ using literature and empirical tuning.

For the classification step, all detection methods were combined with a feedforward neural network that had been trained to distinguish between in-control and out-of-control process conditions. The training sample consisted of 600 observations (half in-control and half shifted), and the test sample consisted of 400 observations (again, equal division). Faulty samples were generated through mean shifts added to the in-control data to simulate changes in the mean of the process.

The shift vectors are utilized to characterize variations within one or more process variables that comprise small shifts as well as large shifts.

(0, 0, 0)	(no shift)
(0.1, 0,0)	(small univariate shift)
(0.2, 0, 0)	
(0.5, 0, 0)	(moderate univariate shift)
(0, 0, 3)	(large univariate shift)
(5, 0, 0)	(extreme univariate shift)
(0, 8, 0)	(extreme univariate shift)
(0.1, 0.1, 0.1)	(small multivariate shift)

(0.2,0.2,0.2)

(0.5, 0.5, 0.5) (moderate multivariate shift)

(3,3,3)

(6, 6, 6) (extreme multivariate shift)

Of note is that the work also considers the effect of differing underlying distributions of the data. The runs were conducted on four distributions: the multivariate normal (chosen as the base), the multivariate t-distribution with degrees of freedom equal to 3 and 5 (introducing heavy tails), the multivariate gamma distribution (introducing skew), and the multivariate log-normal distribution. They are typical types of data experienced in real-life production. For gamma-distributed variables, centering and scaling were done to have zero mean and unit variance for meaningful comparison with the other distributions. Equations for pdf each distribution are as follows,

Multivariate normal distribution,

$$f(x) = \frac{1}{(2\pi)^{p/2} |\Sigma|^{1/2}} \exp\left(-\frac{1}{2}(x - \mu)' \Sigma^{-1}(x - \mu)\right) \quad (4.6)$$

where $-\infty < x_i < \infty$ for $i = 1, 2, \dots, p$.

$$f(x) = \frac{\Gamma\left(\frac{v+p}{2}\right)}{\Gamma\left(\frac{v}{2}\right) v^{p/2} \pi^{p/2} |\Sigma|^{1/2}} \left[1 + \frac{1}{v}(x - \mu)^T \Sigma^{-1}(x - \mu)\right]^{-\frac{v+p}{2}} \quad (4.7)$$

where v is degree of freedom, and p is dimension of the data, μ is mean vector and Σ is covariance matrix.

$$f(x) = \frac{1}{\prod_{i=1}^p x_i (2\pi)^{p/2} |\Sigma|^{1/2}} \exp\left(-\frac{1}{2}(\log x - \mu)^T \Sigma^{-1}(\log x - \mu)\right)$$

$$all \in x_i > 0 \quad (4.8)$$

$$f(x) = 2\phi_p(x; \mu, \Sigma)\Phi(\alpha^T \Sigma^{-1}(x - \mu)) \quad (4.9)$$

where, ϕ_p PDF of multivariate normal distribution, Φ is CDF of the univariate standard normal, and α is shape parameter controlling skewness.

Once a sample has been generated, its fault label (in-control or out-of-control) was assigned, and a feature vector was formed to feed into the neural network. This input vector consisted of two components: the mean-shifted process vector, and the RAM contribution vector, each component d_j being the effect of removing variable j from the control statistic. These two vectors were merged into a single vector of length $2p$ and used to train a binary classifier using a feedforward neural network. The architecture consisted of one hidden layer of five neurons, a logistic sigmoid output unit, and backpropagation training with a weight decay regularization parameter of 0.01 to avoid overfitting. Training and testing of each model were performed independently for each distribution and shift scenario to test its reliability under different settings.

The experiment was replicated 1,000 times for each scenario to address variation and obtain statistically consistent results. Classification accuracy for T^2_{nn} . as well as $MCUSUM_{nn}$. models in every repeat were recorded. Extreme performance was addressed by calculating mean accuracy and standard deviation over repeats. Such parameters allow proper and strict comparison of the performance of each model under different conditions and give an idea of their robustness, sensitivity, and likely use in real-time fault monitoring.

4.5 Performance of evaluation for result simulation T_{nn}^2 and $MCUSUM_{nn}$

This section gives the performance outcomes of the new $MCUSUM_{nn}$ model compared to the standard T_{nn}^2 model. Comparison was carried out for various data distributions (Normal, t-distribution with 3 and 5 df, Gamma with shape parameters 2 and 4, and Log-normal) and under various mean shift scenarios. Comparison of models was done based on classification accuracy and standard deviation (SD) for 1,000 runs of simulations.

Tables are ordered by distribution, and there is a table that indicates model accuracy and standard deviation by shift case. The baseline is in controlling the processes at 50% and we monitor and detect only out of control cases (OOC).

4.4.1 Normal distribution

For Table 4.1, $MCUSUM_{nn}$ also outperforms T_{nn}^2 under Normality for small to moderate shifts (e.g., (0.1,0.1,0.1), (0.2,0.2,0.2), and (0.5,0.5,0.5)), up to 92% accuracy. T_{nn}^2 improves only with large shifts (e.g., (6,6,6)), for which both techniques approach perfect detection. This proves that $MCUSUM_{nn}$ provides earlier detection capability, an essential requirement of preventive control systems.

Distribution	Normal			
Method	T_{nn}^2		$MCUSUM_{nn}$	
Shift	Accuracy	SD	Accuracy	SD
0,0,0	0.5000	0.0000	0.5035	0.0128
0.1,0.1,0.1	0.5534	0.0179	0.704	0.1165
0.2,0.2,0.2	0.6232	0.0209	0.8715	0.0917

0.5,0.5,0.5	0.8145	0.0182	0.9209	0.1076
3,3,3	1.0000	0.0001	0.9517	0.1131
6,6,6	1.0000	0.0000	0.9591	0.1057

Table 4.1: Accuracy under Normal Distribution

4.5.2 T distribution

For Table 4.2, performance comparison for heavy-tailed t-distribution ($df = 5$). With heavier tails, $MCUSUM_{nn}$ performs well even at small shifts (63.34% at shift (0.1,0.1,0.1), while T^2_{nn} remains at near-chance levels (54.49%). This indicates the capability of $MCUSUM_{nn}$ to tackle outliers and data variability, which are traditionally linked with standard T^2 computation.

Distribution	T(5)			
Method	T^2_{nn}		$MCUSUM_{nn}$	
Shift	Accuracy	SD	Accuracy	SD
0,0,0	0.5000	0.0000	0.5033	0.0149
0.1,0.1,0.1	0.5449	0.0152	0.6334	0.0985
0.2,0.2,0.2	0.5982	0.0195	0.8319	0.1019
0.5,0.5,0.5	0.7646	0.0199	0.9065	0.1049
3,3,3	0.9990	0.0018	0.9447	0.1222
6,6,6	1.0000	0.0004	0.9516	0.1171

Table 4.2: Accuracy Under The T-distribution ($df = 5$)

As tails become more extreme, $MCUSUM_{nn}$ gets better still, with especially good performance at shifts like (0.5,0,0) and (0,0,3). With challenging conditions too, it detects

moderate changes more effectively than T^2_{nn} , which lags until extremely large shifts (≥ 5 units). This demonstrates $MCUSUM_{nn}$'s robustness to noisy environments.

Distribution	T (3)			
Method	T^2_{nn}		$MCUSUM_{nn}$	
Shift	Accuracy	SD	Accuracy	SD
0,0,0	0.5	0	0.5039	0.0175
0.2,0,0	0.5417	0.0175	0.6192	0.1046
0.5,0,0	0.63	0.0206	0.8748	0.0931
0,0,3	0.9659	0.0101	0.9792	0.0506
5,0,0	0.9927	0.0048	0.9829	0.0562
0,8,0	0.9976	0.0028	0.9868	0.0499
0.5,0.5,0.5	0.7326	0.0195	0.8807	0.1036
6,6,6	0.9988	0.0019	0.9472	0.1195

Table 4.3: Accuracy Under The T-distribution (df = 3)

4.5.3 Gamma distribution

Distribution	Gamma (2,1)			
Method	T^2_{nn}		$MCUSUM_{nn}$	
Shift	Accuracy	SD	Accuracy	SD
0,0,0	0.5000	0.0000	0.5050	0.0159
0.1,0.1,0.1	0.8676	0.1916	0.7973	0.1756
0.2,0.2,0.2	0.8849	0.1791	0.8075	0.1721
0.5,0.5,0.5	0.8976	0.1645	0.7965	0.1772

3,3,3	0.8855	0.1756	0.8032	0.1729
6,6,6	0.8844	0.1740	0.8032	0.1748

Table 4.4: Model Accuracy Under Gamma Distribution (shape = 2, rate = 1)

With great skewness, the performance of both models is competitive in all shifts. T^2_{nn} has superior figures, particularly at moderate and large shifts, perhaps due to the symmetrical variance structure of simulated data. Nevertheless, $MCUSUM_{nn}$ remains close all the time with less variable standard deviations for repeated runs, suggesting less performance variability.

Distribution	Gamma (4, 1)			
Method	T^2_{nn}		$MCUSUM_{nn}$	
Shift	Accuracy	SD	Accuracy	SD
0,0,0	0.5	0	0.5045	0.0148
0.2,0,0	0.9765	0.0893	0.9548	0.1119
0.5,0,0	0.9735	0.0975	0.9605	0.1069
0,0,3	0.9737	0.0972	0.9557	0.1133
5,0,0	0.9764	0.0915	0.9632	0.1005
0,8,0	0.9702	0.1005	0.9587	0.1086
0.5,0.5,0.5	0.8819	0.1811	0.8113	0.1726
6,6,6	0.8933	0.1694	0.796	0.1783

Table 4.5: Accuracy Under Gamma Distribution (shape = 4, rate = 1)

Detection accuracy in less skewed Gamma data. Both models are good when skewness decreases, with T^2_{nn} having better accuracy in most scenarios. But for small shifts and

more complex scenarios like (0.5,0.5,0.5), $MCUSUM_{nn}$ still provides competitive detection. The data suggests that T^2_{nn} benefits from symmetric and well-behaved variance, while $MCUSUM_{nn}$ is more stable under irregular shifts.

4.5.4 Log normal distribution

Distribution	Lognormal			
Method	T^2_{nn}		$MCUSUM_{nn}$	
Shift	Accuracy	SD	Accuracy	SD
0,0,0	0.5	0	0.505	0.0237
0.1,0.1,0.1	0.5501	0.0129	0.5691	0.0603
0.2,0.2,0.2	0.6056	0.0162	0.6691	0.1072
0.5,0.5,0.5	0.7623	0.0192	0.8507	0.1093
3,3,3	0.9965	0.0034	0.9304	0.1184
6,6,6	0.9979	0.0027	0.939	0.1217

Table 4.6: Accuracy Under Log-normal Distribution

For above Table 4.6 shows performance in log-normally distributed data with high skewness. In extreme skew situations, $MCUSUM_{nn}$ demonstrates its best feature. Although T^2_{nn} is poor with small shift detection (e.g., 55% at (0.1,0.1,0.1)), $MCUSUM_{nn}$ is at 57–67%, which increases incrementally to well above 85% at (0.5,0.5,0.5). Even for large shifts like (3,3,3) and (6,6,6), $MCUSUM_{nn}$ is very robust, only just behind T^2_{nn} , which benefits from the large value.

4.5.5 Graphical results

The following Figure 4.3 displays the accuracy of $MCUSUM_{nn}$ and T^2_{nn} methods in a normal distribution. For minor and moderate shifts of (0.1,0.1,0.1) and (0.2,0.2,0.2), $MCUSUM_{nn}$ is distinctly superior to T^2_{nn} , detecting the out-of-control state more precisely with much higher accuracy.

For large shifts of (3,3,3) and (6,6,6), both methods achieve almost flawless accuracy, but T^2_{nn} is closest to flawless detection slightly more reliably. This means that $MCUSUM_{nn}$ is more sensitive to early or small shifts, while T^2_{nn} performs well when the shift is significant.

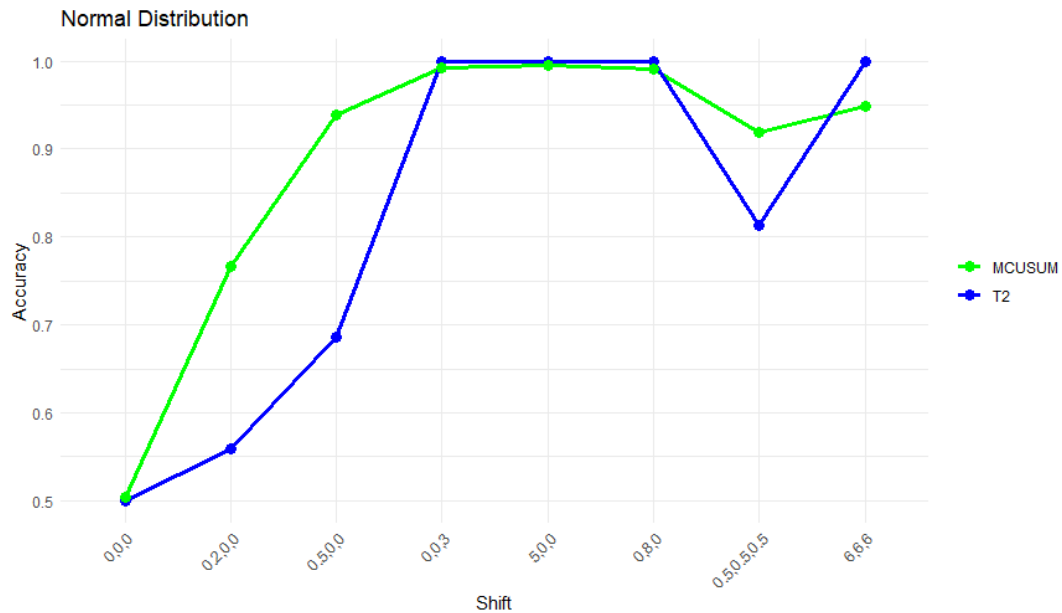


Figure 4.3: Comparison of Accuracy Under the Normal Distribution

The below Figure 4.4 shows model performance on a heavy-tailed t-distribution with 5 degrees of freedom. $MCUSUM_{nn}$ clearly outperforms T^2_{nn} on all small to moderate shifts (especially (0.2,0.2,0.2) and (0.5,0.5,0.5)), with greater accuracy consistently.

For large changes like (3,3,3) and (6,6,6), the gap narrows and T^2_{nn} equals or just surpasses $MCUSUM_{nn}$, demonstrating its performance under large changes. The result re-affirms that $MCUSUM_{nn}$ is better suited for early fault detection in non-normal conditions and that T^2_{nn} remains a good benchmark for large deviations.

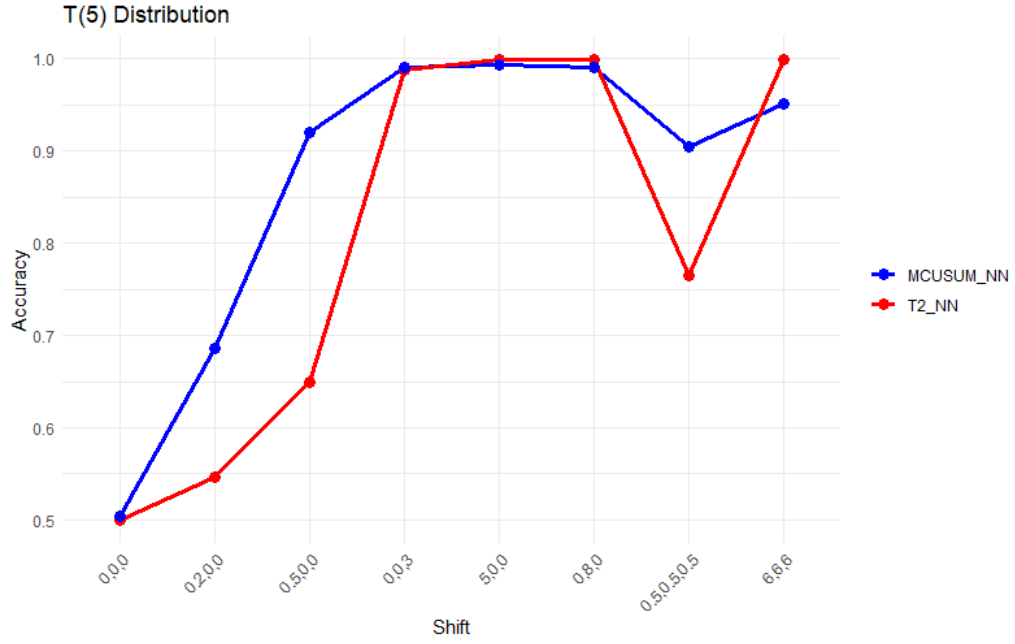


Figure 4.4: Accuracy Comparison Under the T (5) Distribution

The Figure 4.5 Under the lognormal distribution, which introduces skewness. $MCUSUM_{nn}$ is better under early and moderate shift detection, especially up to (0.5,0.5,0.5), where $MCUSUM_{nn}$ always does better than T^2_{nn} .

Both methods achieve high accuracy in extreme shifts, but T^2_{nn} marginally achieve higher values, especially at (6,6,6). Generally, $MCUSUM_{nn}$ is useful when tracking non-normal skewed data for small or moderate process changes, thus consolidating its efficacy as a stable fault detection method in non-normal conditions.

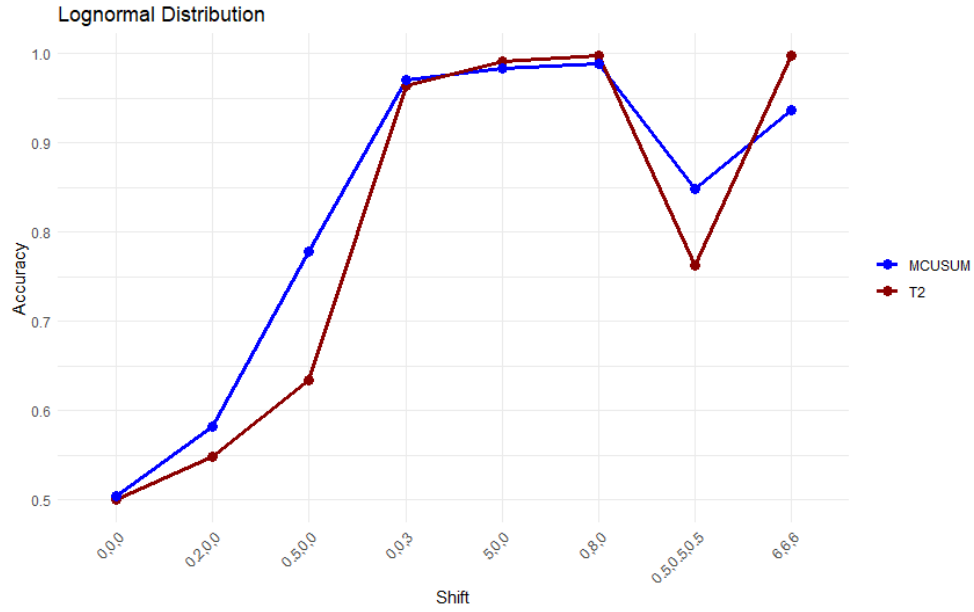


Figure 4.5: Accuracy Comparison Under the Lognormal Distribution

4.6 Chapter 4 Conclusion

Throughout this chapter, an extensive simulation study was presented to compare the performance of the novel $MCUSUM_{nn}$ monitoring scheme, which integrates Crosier's MCUSUM chart and a neural network classifier, with that of the traditional T^2_{nn} approach for various types of data distributions and several shift scenarios.

The simulation results indicated that $MCUSUM_{nn}$ is more effective than T^2_{nn} in detecting small and moderate process shifts, particularly for non-normal distributions such as the t-distribution, gamma, and lognormal. MCUSUM's ability to accumulate small deviations over time gives it a clear advantage in early fault detection, which is extremely crucial in real-world quality monitoring systems where subtle shifts invariably herald catastrophic failures.

In the cases of large shifts, such as shift vectors (3,3,3) and (6,6,6), both procedures worked nicely. However, T^2_{nn} was a better than $MCUSUM_{nn}$ in extreme cases, particularly under symmetric distributions like the normal distribution. This finding aligns with the strong points of the Hotelling T^2 chart, which is very sensitive to large, abrupt changes.

The other salient characteristic of the suggested $MCUSUM_{nn}$ model is robustness. It maintained good detection accuracy across various types of distributions, with immunity to non-normality, skewness, and heavy-tailedness. The utilization of RAM-based d-values as inputs to the neural network enhanced the diagnostic capability of the system, which facilitated the identification of the variables responsible for the shifts.

These findings were supported by the graphical presentations, which easily illustrated $MCUSUM_{nn}$ outperforming in the case of early or moderate shifts, with T^2_{nn} only performing competitively when shifts were large, and data followed a symmetric distribution.

Overall, this chapter confirms that $MCUSUM_{nn}$ is a powerful and flexible tool for multivariate process monitoring. It offers improved detection power for subtle changes, strong performance across diverse data environments, and interpretable diagnostics. The method is especially recommended for applications where early detection is critical and where process data may not strictly follow normality assumptions.

CHAPTER 5

CONCLUSION

This thesis seeks to investigate the application of neural network-based techniques for Control Chart Pattern Recognition (CCPR) to address the limitations of traditional statistical process control methods under non-normal data distribution. The research work is structured into four main chapters, each building on the previous one to provide an extensive review of theoretical and application streams of CCPR in modern industrial quality monitoring.

For chapter (1) It highlighted the shortcomings of traditional control chart approaches, above all their assumption-based nature—and posited neural network models as a plausible replacement for more adaptive and robust quality monitoring. The chapter further defined the purpose of the research clearly, presented the guiding questions, and also presented the scope and the relevance of the study in applied statistics and industrial application.

The second chapter integrated findings from over two decades of research, noting developments from basic ANN models towards sophisticated models like CNNs, RNNs, and ensemble models. The chapter also offered a bibliometric snapshot, mapping research patterns, collaborations, and publication hotspots. Notably, the chapter identified significant research gaps like issues related to data imbalance, non-interpretability, computational inefficiency, and no standardized assessment systems. These findings guided the methodology choices in subsequent chapters.

For chapter (3), neural network for control chart pattern recognition explained the primary technical contribution of this research through comparison of various neural network

architectures in recognizing six fundamental control chart patterns: normal, upward shift, downward shift, upward trend, downward trend, and cyclic. A comprehensive simulation study was conducted with data sets generated from normal and non-normal distributions (gamma, t-distribution, and log-normal), mimicking actual industrial data conditions. The performance of Feedforward Neural Networks (FNN), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and a hybrid CNN-RNN model were compared in terms of different metrics like accuracy, precision, sensitivity, specificity, and F1-score.

The findings in Chapter (3) depicted that FNN models consistently outperformed other architectures, particularly in non-normal distributions. The RNN and CNN models demonstrated ability in identifying temporal and spatial patterns respectively but suffered loss of performance in heavy-tailed and skewed data. The hybrid CNN-RNN model offered a balance between sequential and spatial learning and excelled at identifying trend and cyclic patterns but was slightly less consistent overall than FNN. This comparative analysis confirmed that model selection in CCPR must consider the nature of the data distribution and the specific pattern recognition requirements.

Finally, chapter (4) Integration of MCUSUM Control Chart and Neural Network for Detecting Abnormal Shift Processes continued the research by integrating neural networks with Multivariate Cumulative Sum (MCUSUM) control charts to enhance the detection of small shifts in multivariate industrial processes at an early stage. The integration allowed the capabilities of neural networks, i.e., their capability to handle non-linearity and distributional strangeness to be matched with MCUSUM chart's cumulated sensitivity. This hybrid approach was particularly valuable in identifying subtle changes in process

behavior that are typically missed by traditional multivariate normality and independence-assuming charts.

In all chapters, the general theme of this thesis has been the promotion of process monitoring techniques through the adoption of artificial intelligence and deep learning. Research has demonstrated that when well designed and experimented upon, neural network-based CCPR models can by far outperform traditional methods, especially in complex, noisy, and non-ideal industrial processes. In addition, the findings provide actionable suggestions to quality control professionals on model selection, feature engineering, and evaluation method for adopting AI-based monitoring systems.

In conclusion, this study has made both methodological and practical contributions in statistical quality control. This study has illustrated that neural networks specifically FNNs achieve high accuracy and robustness for CCPR classification problems even in non-normal distribution environments. The integration of neural networks with MCUSUM charts also enhances the toolkit for quality practitioners and engineers for proactive fault detection and real-time process monitoring. Although challenges related to model interpretability, computational requirement, and class imbalance remain to be tackled, this research provides a strong foundation for further exploration and development of adaptive, intelligent quality control monitoring systems. With industries increasingly adopting smart manufacturing and Industry 4.0 technologies, the relevance and demand for AI-based CCPR solutions will only keep increasing.

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VITAE

Name : Zakariye Ali

Nationality : Somali

Date of Birth : 11/09/1998

Email : hayaan2040@gmail.com

Address : Km4 street -Mogadishu -Somalia. Postal code: 004

Academic Background : M.Sc. Applied Statistics, KFUPM, Saudi Arabia, 2025.
BSc. Statistics and Planning, MU, Somalia, 2021.

List of papers :

- Zakariye Ali, Muhammad Riaz, JIMOH OLAWALE AJADI, A Systematic Review and Bibliometric Analysis of Neural Networks for Control Chart Pattern Recognition (Submitted).
- Zakariye Ali, Muhammad Riaz, JIMOH OLAWALE AJADI, Neural Network Models for Control Chart Pattern Recognition: A comparative performance analysis (Submitted).
- Zakariye Ali, Muhammad Riaz, JIMOH OLAWALE AJADI, Integrating Multivariate control charts and Neural network (Under processes).