Intelligent Automation System for Critical Analysis of Sewing Thread Breakage and Effects to Enhance Productivity

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Abstract

Sewing thread Breakage is one the leading cause for damage the garments productivity all over the world. In Bangladesh, various factories face the similar problem. The factors that are affecting the breakage are depended on the properties and quality of the yarn. Except for the thread quality, some other features also involve to breakage the thread. Types of the fabric, the weight of the unit area, the thickness of the fabric, thread count, strength, elongation % of the sewing thread and Needle number, machine speeds, yarn tension, stitch per inch are major factors for thread breakage. An appropriate prediction mechanism technique can apply to significantly reduce this problem. In this work, we have proposed an intelligent system that can make an effective prediction of a possible sewing thread breakage. Eleven (11) features and nine (09) well known supervised machine learning algorithms we have applied to analyze the prediction accuracy percentages. The overall process has been categorized into four stages. Stage 1: we have provided a comprehensive literature review where we summarize various related machine learning algorithms. Stage 2: Thread breakage data have been collected by the survey questionnaires and practical observations from the different apparel industries of Bangladesh. Stage 3: The feature factors data have been filtered and processing. Finally, fed the data to suitable machine learning algorithms to determine the predictive model and accuracy percentage of sewing thread breakage. ANN (artificial neural network) multilayer perceptron scaling accuracy specified for 11 functions, Comparative supervised machine learning, decision tree (J48), random forest, stochastic gradient, and sequential optimization have 100% accuracy, and with other classification algorithms such as Perceptron Multilayer, accuracy (99.80%) and logistic regression (98, 40%). Unlike Naive Bayesian Naive Bayesian (94%) has been updated. In Bangladesh, most companies are unaware of the cost of refining yarn and remanufacturing productivity. The main reasons for thread cutting are the lack of skills associated with production and inexperienced labor This intelligent system can predict the condition of a seamstress by measuring simple information that plant personnel find useful. Finally, it will improve productivity and the economy as a whole.

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Chapter 1

Introduction

Nowadays, information technology, artificial intelligence (AI) has revolutionized the field of engineering, physics, medicine, Textile and management. Generally, mathematical models are used to solve the problems and decision-making process. It is the key principle of AI [1]. Always focus is on achieving good quality, reduced cost, appropriate information management, statistical process control, just-in-time manufacturing, and computer-integrated manufacturing in addition to the volume of production [2] [1] [3]. AI is increasingly used in apparel design, pattern construction, production planning, marker planning, sewing floor, sales forecasting, and supply chain. Several technologies are used in artificial intelligence, such as special systems, artificial neural networks (ANN), fuzzy logic , genetic algorithms, evolutionary strategies, artificial immune systems, and multi-agent systems. To produce sewing in clothing manufacturing [2]. AI is a field of computer science, human intelligence, and human sensory capabilities that can help the industrial economic progress of the world. Automation systems depend on knowledge to sustain their functionalities and machine learning offers such a knowledge [4]. Conventional computers are the lack ability to learn, and this hampers innovation productivity.

1.1 Objectives of Research Work

Waste of time and process work is a serious problem in the apparel industry. Automated models can be used in the garment industry to predict wire breakage. Automation models can help improve productivity and reduce process costs.

- To Fill out a questionnaire for collecting sewing thread cutting data from the Apparels.
- To Development of sewing thread cutting prediction system.
- To Analyze performance on different amounts of data using a variety of machine learning algorithms.
- To builds reliable raw data on Bangladesh's clothing industry.

1.2 Present Scenario of the Clothing Industries

The Garment components are sewn by skilled workers and compressed and checked for quality of finished garments [5]. The Many factors related to the success of the apparel industry, such as lead time, product quality, production cost, worker efficiency ratio, reduced manufacturing or reworked scrap systems, have influenced global issues. Due to global problems in the apparel industry, the World Trade Organization has published the top ten scenarios for apparel exports. China ranked first in apparel exports, with a total export value of $116 billion. Likewise, Bangladesh received $33.16 billion in apparel exports, ranking second among the world's top 10 exporting countries [6]. Repair in the apparel industry is a common task that interferes with smooth production and targets poor quality products. It affects the entire business economy [7]. Sewing thread cutting is a major disadvantage of product quality and a decrease in productivity. This always brings added value to the product.

Figure 1.1: Top Ten Exporters of Clothing-2019

Taking into account the global issues of the apparel industry, the World Trade Organization has published 10 major apparel export scenarios in figure-1.1. China ranks first in apparel processing exports, with a total export value of $116 billion. Similarly, Bangladesh received USD 3.36 billion in apparel exports and ranked second among the world's top 10 export processing countries [8].

The lower quality products are hampered productivity. These errors can be repaired, which can lead to rework or reimbursement resulting in errors. Repair in the apparel industry is a common task affecting the entire plant economy by disrupting smooth production and focusing on poor quality products. Operation is an important issue of poor-quality products and low productivity. Cutting sewing thread is a major disadvantage of product quality and a decrease in productivity. This always brings added value to the product.

1.3 Financial Situation of Apparels Industries

During the 2018-2019 fiscal year, nearly 84% of foreign currency came from Bangladesh (RMG), and more than 4 million people worked in the apparel industry [9]. Basically, In essence, it remains a competitive business environment in the apparel industry, as industrialists always want to offer different products based on consumer desires. Work measurement techniques were used to record the time and speed of the elements under specific conditions[10]. Employee performance, tactics and manufacturing errors are the link between productivity. Sewing errors cannot be completely reduced, but any technique can be improved to reduce sewing defects. This concession is very important in minimizing our monthly income loss. The factory analyzed thread sewing costs and rework problems. It also includes applications for pattern design, production planning and management (PPC), manufacturing marking, sewing automation, sales forecasting, appropriate recommendations, SCM and retail, and more. The optimization classical takes into reason workers' skill stages as well as the limitation on the amount of apparatuses at each station (employee) [11].

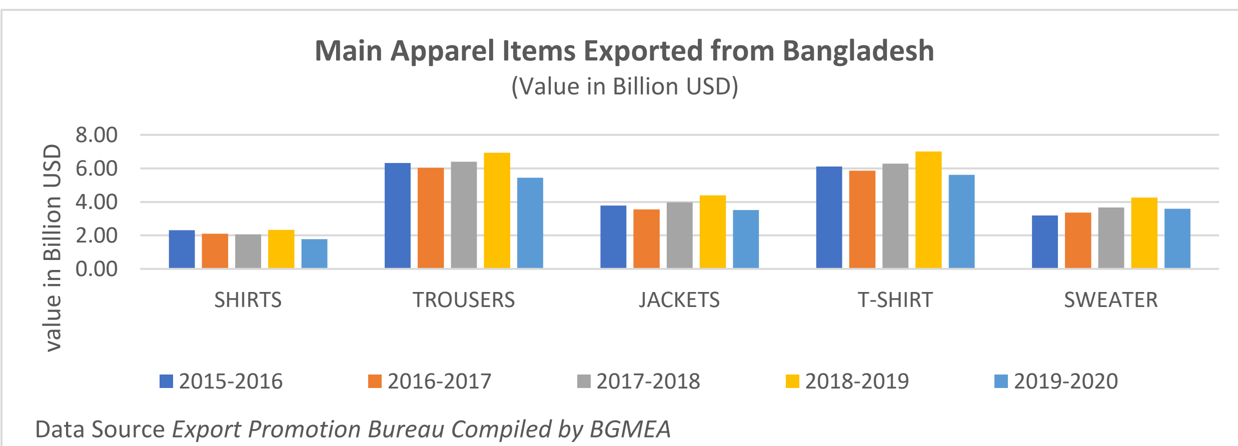

Figure 1.2 Main Apparel Items Exported from Bangladesh

Table 1.1: Average Production Process Cost per Month of different items

Items Name	Production per hour (PCS)	Production per Month (PCS)	Cost of Making Per Pcs (CM)	Total Process Cost	Average Process Cost
T-shirt	180	46800	$1.10	$51,480.00	$44373.33
Polo Shirt	120	31200	$1.50	$46,800.00	
Trouser	110	28600	$2.00	$57,200.00	
Long Sleeve Woven Shirt	80	20800	$1.50	$31,200.00	
Woven Long Bottom	90	23400	$1.70	$39,780.00	
Denim Long Bottom	85	22100	$1.80	$39,780.00	
			TOTAL COST	$266,240.00	

Table 1.2: Total Re-work cost of different items

Items Name	Rework per hour (PCS)	Rework per Month (PCS)	Avg. Time per pcs (Min)	Total Time Need per Month (Min)	Rework Cost Per Min (Dollar)	Total Rework Cost
T-shirt	4	1040	1.50	1560	$0.660	$1,029.60
Polo Shirt	5	1300	1.21	1573	$0.750	$1,179.75
Trouser	6	1560	2.10	3276	$0.856	$2,804.26
Long Sleeve Woven Shirt	8	2080	1.85	3848	$0.600	$2,308.80
Woven Long Bottom	7	1820	1.70	3094	$0.595	$1,840.93
Denim Long Bottom	5	1300	1.80	2340	$0.638	$1,492.92
					TOTAL COST	**$10,654.94**

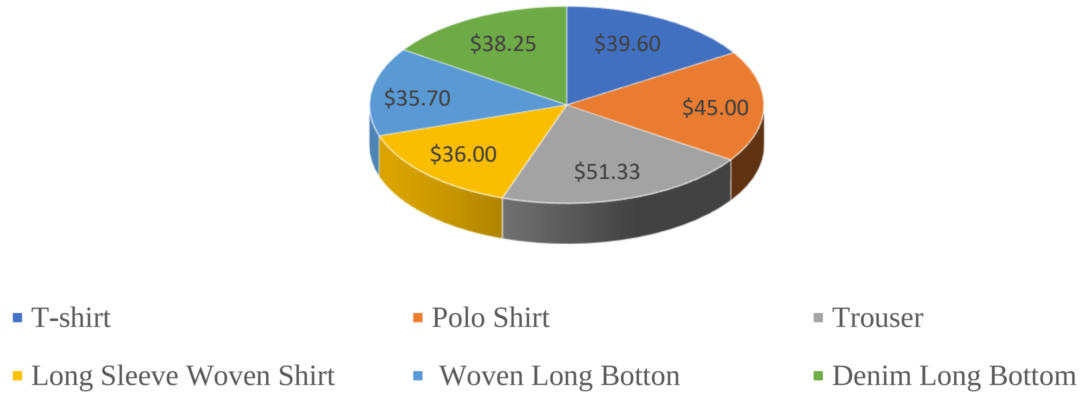

Figure 1.3: Average Production process Cost of Different Items

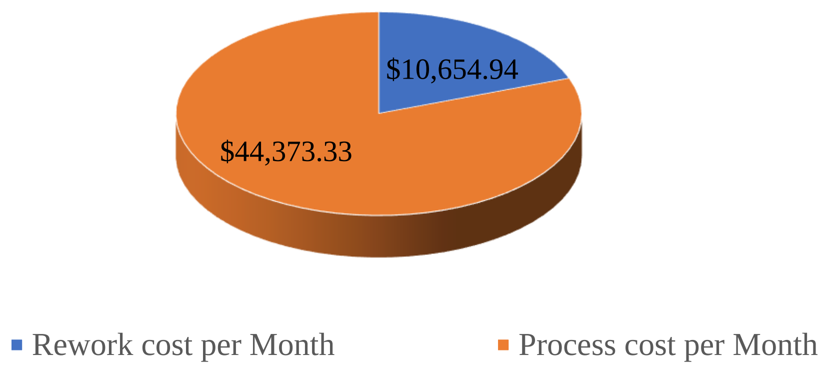

Figure 1.4: Monthly process Price and re-work charge of different clothes

1.4 Organization of the Chapter

This book of research is organized as follows. Chapter 2 describes the background and literature review with various literatures findings. Chapter 3 describes the methodology of this research with existing features & proposed features, proposed model, describes the dataset, and describes the features. Depict the experimental results in Chapter 4. Chapter5 concludes the research with limitation and shows some future work directions. Finally, in chapter 6 discussed about appendix.

Chapter 2

Literature Review and Background

Clothing is one of the basic human needs. Sometimes he shows that his personality is regarded as a human personality, interests, sociality, etc. The clothing manufacturing process from the day of beginning invent is a labor-intensive process, which has not done much progress toward automation. Developing countries are mostly using manual practices in garments, Textile and apparel accessories processing due to more cost of installing automated tool and equipment. There are many obstacles found in garments industries during production. The sewing Thread breakage problem is one of them A good sewing thread should have sufficient tensile strength and twist evenly over the entire length, twisted evenly, and the twisted thread should be treated with a special layer to increase wear resistance during stitching operation and can be spun from staple yarn, filament, or core-spun yarns [12]. In recent years, the focus is on achieving superior quality, cost reduction, relevant Textile management information, statistical process control, rapid production systems and computer-integrated production systems that increase productivity.

2.1 Benefits of Textile Sectors

In the past, the process of making clothes developed into an art, but now it plays an important role in the global economy. The use of artificial intelligence technology in industry increases productivity and reduces errors. During the processes of apparel design, manufacturing and retailing, industrial participants are required to tackle various decision-making problems, such as apparel design, cut order planning (marker making), production scheduling, sales forecasting, and supply chain management (SCM), some of which are making), production scheduling, sales forecasting, and supply chain management (SCM), some of which are very intractable [13]. The technological advancements in the apparel industry include the use of computerized equipment (especially in design, pattern making, and cutting), three-dimensional (3D) scanning technology, integration of wearable technology, advanced material transport systems, automation, and use of robotics or AI.

2.2 Related Research Work of Feature Factors

Table 2.1: Feature Factors Descriptions of research work

SL #	Feature Factors	Writers Name	Reference No	Descriptions
1.	Thread Tension	Shinji Kojima; et.al.	[14]	The sewing thread scale is 0 to 9, low values indicate weak tension, and high values indicate seam strength.
2.	Machine speed (rpm)	Mazari, et.al.	[15]	Apparel Industries used engine speeds of 2400 to 4200 rpm.
3.	Stitch Per Inch (SPI)	Nazakat Ali, et.al.	[16]	The number of stitches to use is 8, 10 and 12 inches for different types of fabric.
4.	Needle Number	Hunter, et.al.	[17]	Two types of sewing needles are used in the garment industry. US needle size and EU needle size.
5.	Thickness of Fabric (mm)	Collier, et.al.	[18]	The Standard Fabric Thickness Test Method used for research work was ASTM D1777-96 (2019).
6.	Weight of Fabric (GSM)	Collier, et.al.	[18]	The Standard Fabric weight Test Method used for research work was ASTM D3776/D3776-09a (2017).
7.	Thread Count (Tex)	Midha, et. al.	[19]	This research paper uses polyester core spinning with 50Tex, 60Tex and 100 Tex cotton yarns.
8.	Tensile Strength (cN/tex)	Midha, et. Al.	Fig-3.4, 3.5 & 3.6, [19]	The sewing holder's tensile strength is higher than 100tex and 60tex, but 50tex is lower.
9.	Sewing Thread Elongation Percentage.	Midha, et. Al.	Fig-3.4, 3.5 & 3.6, [19]	The elongation is 100tex high and 50tex is high and 60tex is low percentage length.
10.	Different Types Fabrics.	Bertaux, Emilie Lewandowski, et.al.	[20]	We used a variety of fabrics such as Jersey, Pique, Lacoste, Fleece, Double Lacoste, Twill, Slub Denim, Regular Denim to get the best research results.

2.3 Sewing Thread Breakage

Figure 2.1 Image of Sewing Thread Breakage

The sewing thread cutting is shown in Figure 2.1, the fabric type is 100% cotton, the weight is 280g/m2, the sewing thread is 60Tex, and the sewing thread tension was 6 thread tensions.

2.4 Feature Factors of Sewing Thread Breakage

Thread tension factor, machine speed, stitches per inch, fabric type, fabric weight, thread count, tensile strength, and thread elongation are the main reasons for sewing thread cutting. Moreover, more thread breakages show more quality fall and increase operational reworks that is also adding cost on product.

Sewing Tension (ST): The thread tension is used on a scale of 0 to 9, and a lower value indicates a weaker tension, and a higher value indicates a tighter seam.. If the scale rotates clockwise the value shows higher and the top sewing thread shows loose thread and the bobbin thread shows tight.

Speed of Machine (rpm): We have observed that the apparel industries apply in different machine speed based on fabric types and fabric thickness. Generally, we have found sewing machine speed from 2400 rotation per minute to 4000 rotation per minute.

Stitch Per Inch (SPI): In general, the number of stitches used for different fabrics will gradually vary with different categories (8, 10 and 12) of fabric stitches per inch.

Sewing Needle Number (NN): There are two sorts of sewing Needle estimate applies within the Attire businesses. American needle estimate and European Needle measure. Needle estimate alludes to the thickness of the needle breadth and essentially decides the weight or thickness of the texture that can be sewing. Smaller sizes refer to smaller (thinner) needle sizes used for lighter fabrics. Higher numbers indicate larger (thick) needles used for heavier fabrics.

There are various sizes, but the most common are SINGER® 11/80 (for light fabrics), 14/90 (for medium fabrics) and 16/100 (for medium to high fabrics). There is also a size 9/70 available for very light weight fabrics (chiffon, lace, etc), and a size 18/120 for heavy weight fabrics (upholstery, etc). The needle size is expressed in two digits because it uses two different measuring systems: the US and Europe (imperial/metric).

Fabric Thickness (mm): The Standard Fabric Thickness Test Method used for research work was ASTM D1777-96 (2019).

Fabric Weight (GSM): The Standard Fabric weight Test Method used for research work was ASTM D3776/D3776-09a (2017).

Sewing Thread Count (Tex): Polyester core spun with cotton wrap sewing threads 50Tex, 60Tex and 100 Tex are applied for this research work.

Tensile Strength of Thread (cN/tex): The Tenacity is the unit of tensile strength, which means force per unit linear density of a yarn. This is express as centinewton force per tex (cN/tex). We have observed the tenacity of sewing thread from 4.50 CN/Tex to 18.25 CN/Tex. Generally, Lower tenacity of sewing thread is applied for low GSM and low thickness of the fabric.

Sewing Thread Elongation Percentage (El%): The expansion rate appears higher in 100 Tex and 50 Tex but 60 Tex speaks to less prolongation rate.

Different Type of Fabrics: We used a variety of fabrics such as Jersey, Pique, Lacoste, Fleece, Double Lacoste, Twill, Slub Denim, Regular Denim to get the best research results.

2.4.1 Equation Standard Minute Rate of Apparels

$$1. Standard\ Minute\ Rate\ (SMR) = \frac{\text{(Daily Cost of wages)}}{(Available\ working\ Munite\ per\ Day)}\ X\ Efficiency\ \% \ldots \ldots (i)$$

Standard Minute Rate (SMR) = (Daily Cost of wages)/(Available working Munite per DayX Efficiency %)

SMR= DCW/(AWM X E%).. 2.2.1

2. Cost of manufacture (CM)per pcs = (Product SAM x Standard minute rate (SMR)

CM = SAM X SMR……………………………………………2.2.2

3. Standard Allowed Minute (SAM) =

(Total Manpower X Total working Minute per Day X Efficiency%)/ (Total Production Output per Day)

SAM = (TM X WMD X E%) /TPD………………………………………2.2.3

2.5 Machine Learning tools Application in Textile

AI is increasingly being used in apparel design, pattern manufacturing, production planning, marker design, sewing workshops, sales forecasting and supply chains. Many AI technologies such as specialized systems, neural networks (NN), fuzzy logic (FL), genetic algorithms (GA), evolutionary strategies (ES), artificial immune systems (AIS), and multi-agent systems (MAS) are maybe used for sewing. AI is a field of computer science that can model human intelligence traits and human sensory abilities[21].

Table 2.2: Various supervised and unsupervised learning algorithms [22]

Machine Learning Algorithms	
Supervised Learning	**Unsupervised Learning**
Decision Tree	K Mean Clustering
Naïve Bayes	Self-organizing Map
Artificial Neural Network (ANN)	Fuzzy C-Mean Clustering
Support Vector Machine (SVM)	Hierarchical Clustering
K-Nearest Neighbor (KNN)	
Random Forest	
Logistic Regression	

2.6 Related Research Work of Machine Learning Algorithm

Table 2.3: The Machine Learning System application in textile Process

Sl	Name of ML Algorithms	Authors Name	Ref. No.	Area of Textile Sectors	Accuracy (%)
1	Voted Perceptron	Chattopadhyay R, et al.	[23]	Color, fiber, and fibrous fibers can be determined using neural networks with the better accuracy.	98.2
2	Decision Tree (J48)	Parvin,et.al.	[24]	A major accident in the textile sector in Bangladesh.	96.36
3	K-Nearest neighbor	Mokhlespour Esfahani, et.al.	[25]	It tests the accuracy of one of these systems, including commercial equipment cost socks and specific equipment cost jackets.	98
4	Logistic Regression	Hui, Chi Leung Ng, Sau Fun	[26]	Researchers show that the performance of industrial fabrics is based on the performance of floats and seams.	89.7
5	Naïve Bayes classifier	Mattmann, et.al	[27]	Researchers discovered the effectiveness of apparel prototypes for gym experiments to explore their potential for rehabilitation and fitness.	97
Un supervised Machine Learning used in Textile.					
6	Fuzzy logic	Vassiliadis, et.al	[28]	A combination of versatile neurovascular frameworks has been created to anticipate the fiber to yarn ratio.	
7	K-mean	Yildirim, et.al	[29]	In the material industry, KNN is utilized to classify the preparation of strands, yarns, and fabrics.	

Chapter 3

Methodology

Studies have been conducted in six garment industries in Bangladesh. The categories of this factory are basic: knitting, weaving, denim. A total of 35 sewing production lines were used and 1200 raw data were collected to define 10 thread cutting registration functions. The data were collected by physical field observation, preparing questionnaire and some data were collected by factory survey. The features of the research work regarding sewing thread Tension, Machine speed, Stitch per inch (SPI), Fabric weight (GSM), Fabric thickness(mm), Needle Number, sewing thread count, Tensile strength, Elongation%, Fabric types of nine varieties and then we have analyzed the sewing thread breakage in 30 days long duration. Our object is to apply machine learning tools in industries so that we can predict the results, whether the sewing thread will be broken or not, through training data and testing data by processing sequence of data Collect, Data processing, Feature Extraction, and Machine learning tools Application.

3.1 Analysis the Problems

From the beginning Sewing thread breakage, defects analysis, altering the operation and re-working processing we have find out from the factories. Industries are highly demurrage for this as a result reduced productivity, wastage time and money. We have decided to find out the problems and prepare a questionnaire to collect causes and effect information. After that Fabric swatch collected from the factory and we have analyzed the properties of sample in the fabric structure and design laboratory to find out the fabric structure. The weight of the fabric gram per square meter (GSM) measured by GSM cutter instruments, Standards Test Methods for Mass per Unit Area (Weight) of Fabric was American Society for Testing Materials (ASTM) D3776, Thickness of fabric in millimeter (mm) tested by digital fabric thickness tester, Standard testing method American Society for Testing Materials (ASTM) D1777, ISO 5084, Sewing thread strength and elongation test we have conducted with universal strength Tester and standard Test method was (BS EN ISO 2062:1995) in the Textile Testing and Quality Control laboratory.

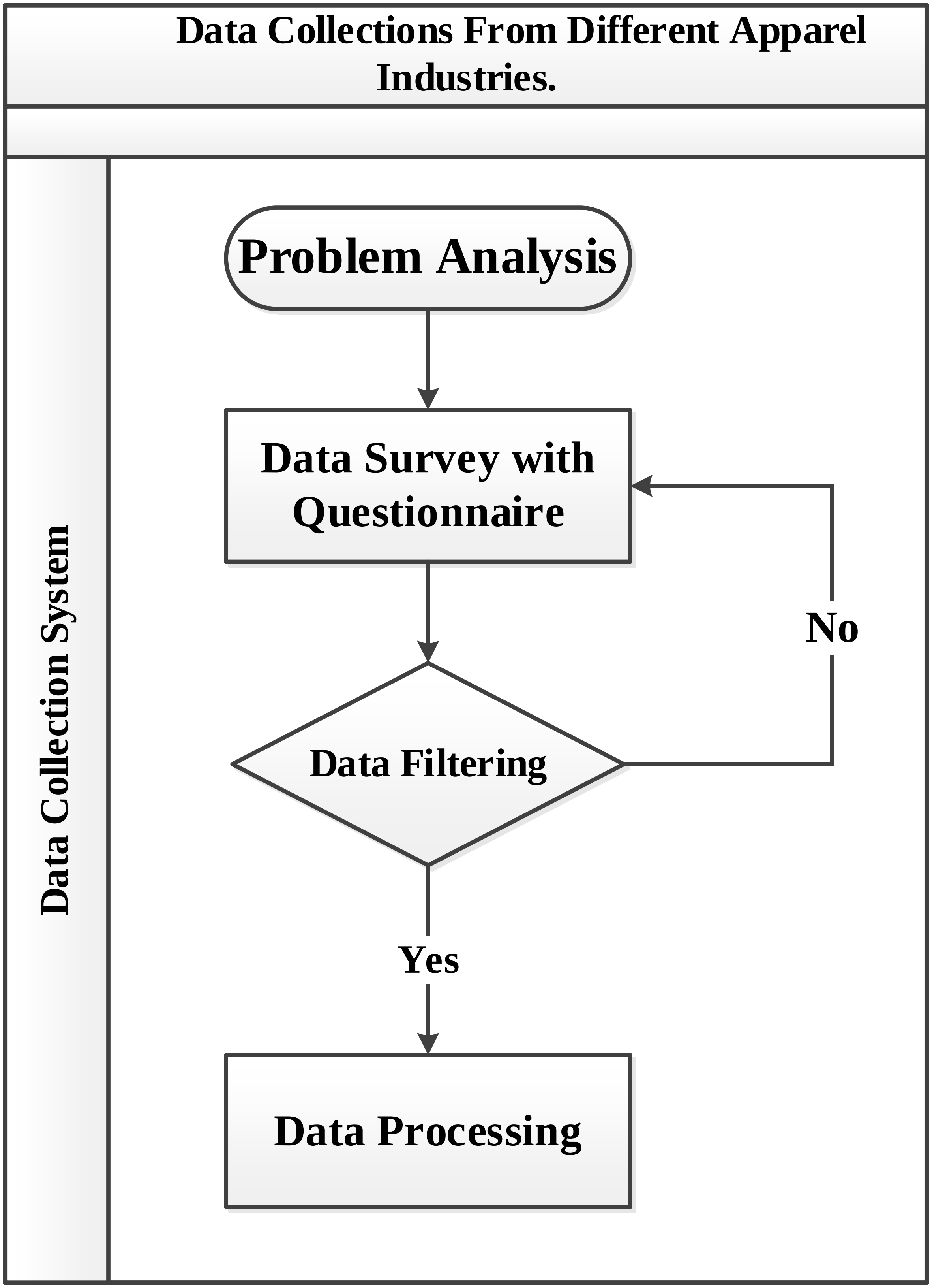

Figure 3.1: Diagram of Data Collection System

Figure: 3.1. Data entry and function extraction are sequenced from 1200 raw data and then prepared for use in machine learning tools, so decisions can be predicted using mathematical models and algorithmic data building based on the input information.

Finally, apparel and garment laboratories and maintenance departments at different factories needed to know the number of stitches per inch (SPI), sewing machine speed (SPM), and number of sewing needles.

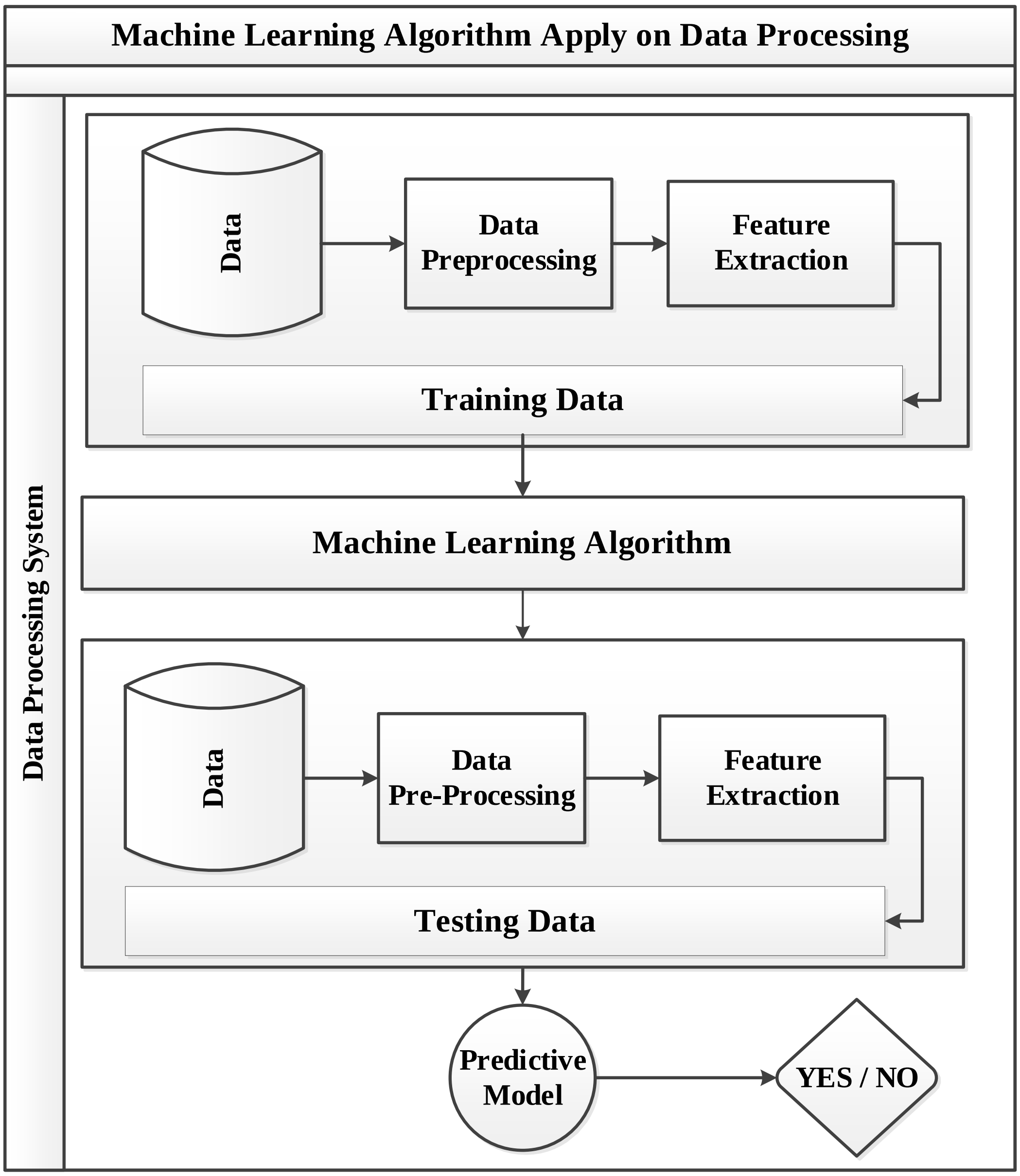

Figure 3.2: Diagram of Data Processing System

Figure 3.2 shows the machine learning data processing algorithm and model prediction. First, the process trains the data and validates the data using machine learning algorithms.

These days, the industry is very anxious because cutting sewing threads, changing jobs and recycling reduce productivity and waste time and money. We have compiled a questionnaire to analyze the problem and collect causal information. Information is now filtered into two categories: meaningful and unused. In terms of data processing, we share two ways to train and test data processing using machine learning tools. When you enter data and extract functions in machine learning, you can predict decisions with mathematical models and construct data algorithms based on the input information.

3.2 Application the Machine Learning Tools

The prediction results were tested using Weka machine learning software. Weka is a Waikato Information Analysis Framework (Weka) developed by the Waikato University of New Zealand. Machine learning algorithms, naive Bayesian algorithms, random forest trees, logistic regression, multilayer perceptron’s, minimal sequential optimization (vectors supported by SMO or SVM), SGD stochastic gradient descent, and J48 to accurately predict various outcomes. Machine learning techniques or classification algorithms can provide reliable results and can be learned from previous calculations when manual data analysis or predictive modeling is not possible. There are mainly two types of data used for machine learning. Raw data is used for unsupervised learning and tagged data is used for supervised learning. Predict sewing thread cutting using various monitoring learning algorithms.

The sewing thread breakage data we have collected practically from the factories. we have categorized in two types as “one” means “yes” and “No” thread breakage mentioned as “zero”. Here we have considered two or more than two breakages, as significant thread breakage and less than two thread breakage means no thread breakage.

Please check (√) honestly based on what you actually have during Garments manufacturing process using following information

1. Sewing Tension Apply in Sewing Machine

Very Lose (below 2)	Lose (2 – 4)	Moderate (4 – 6)	High (6 – 8)	Very High (Above 8)	

2. Speed of Sewing Machine (rpm):

Very Low (below 3000)	Low (3000 – 3500)	Moderate (3500 – 4000)	High (4000 – 4500)	Very High (4500 – 5000)

3. Number of Stitch per Inch:(SPI)

Very Low (below 5)	Low (5 – 8)	Moderate (8 – 11)	High (11 –14)	Very High Above 14)

4. Number of Sewing Needle:(Singer Number System)

Very Fine (below 7)	Fine (7 – 11)	Moderate (11 –15)	Coarser (15 – 19)	Very coarser (Above 19)

5. Thickness of Fabric (mm):

Very Thin (Below 0.1)	Thin (0.1 – 0.5)	Moderate (0.5 – 1)	Coarser (1 – 1.5)	Very Coarser (Above 1.5)

6. Fabric Weight of per unit area (GSM):

Knit	Very Low (Below 100)	Low (100 - 150)	Moderate (150 – 200)	High (200 – 250)	Very High (Above 250)
Woven	Very Low (Below 100)	Low (100 - 150)	Moderate (150 – 200)	High (200 – 250)	Very High (Above 250)
Denim	Very Low (Below 200)	Low (200 - 250)	Moderate (250 – 300)	High (300 – 350)	Very High (Above 350)

7. Strength of Sewing Thread (cN/Tex):

Very Weak (below 4)	Weak (4 – 6)	Moderate (6 – 8)	Strong (8 – 10)	Very Strong (Above 10)

8. Count of Sewing Thread: (Tex)

Very Fine (30)	Fine (40)	Moderate (50)	Coarse (60)	Very coarse (100)

9. Elongation% of sewing thread:

Very Stiff (Up to 5)	Stiff (5 – 10)	Moderate (10 – 15)	Soft (15 – 20)	Very Soft (Above 20)

10. Number of Sewing Thread Breakage per hour:

Nonsignificant (0-2)	Significant (Above 2)	Number of Thread Breakage
0	1	

Name and Organization Signature

3.3 Sewing Thread Breaking Test

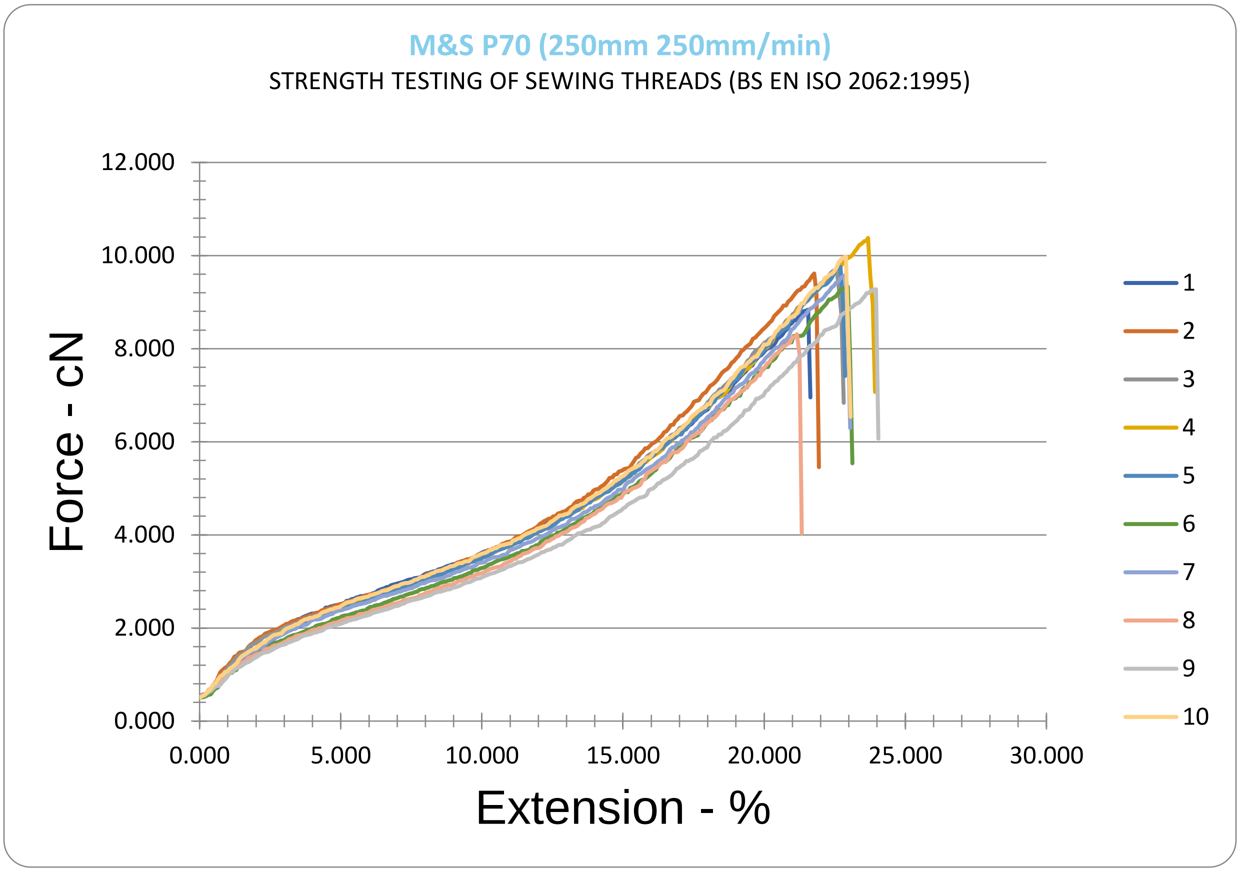

Figure 3.3: Sewing Thread Count of 50 Tex, Strength and Elongation% Test

Figure 3.3 shows the sewing thread breaking load and elongation% of 50 Tex linear density of sewing thread. Where the graph shows that the total number of experiments was ten and breaking load between 8 cN/tex to 11 cN/tex and Sewing thread Elongation% was 21% to 25%.

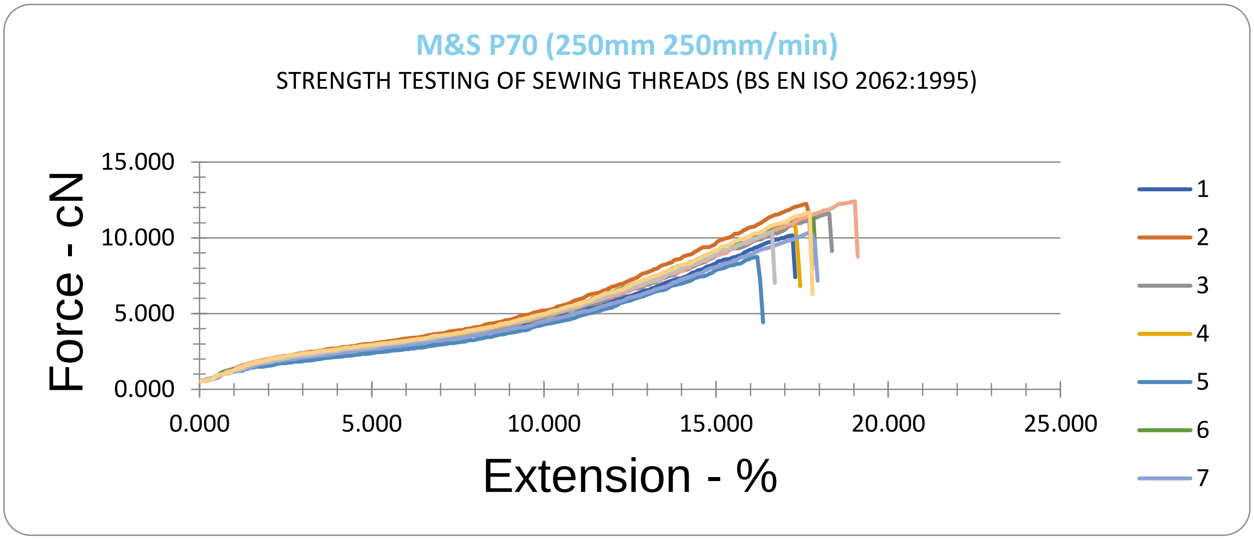

Figure 3.4: Sewing Thread Count of 60 Tex Strength and Elongation% Test

60 Tex linear density of sewing thread breaking load and elongation% shown in Figure 3.4. Where the graph shows that the total number of experiments was ten and breaking load between 9 cN/tex to 13 cN/tex and Sewing thread Elongation% was

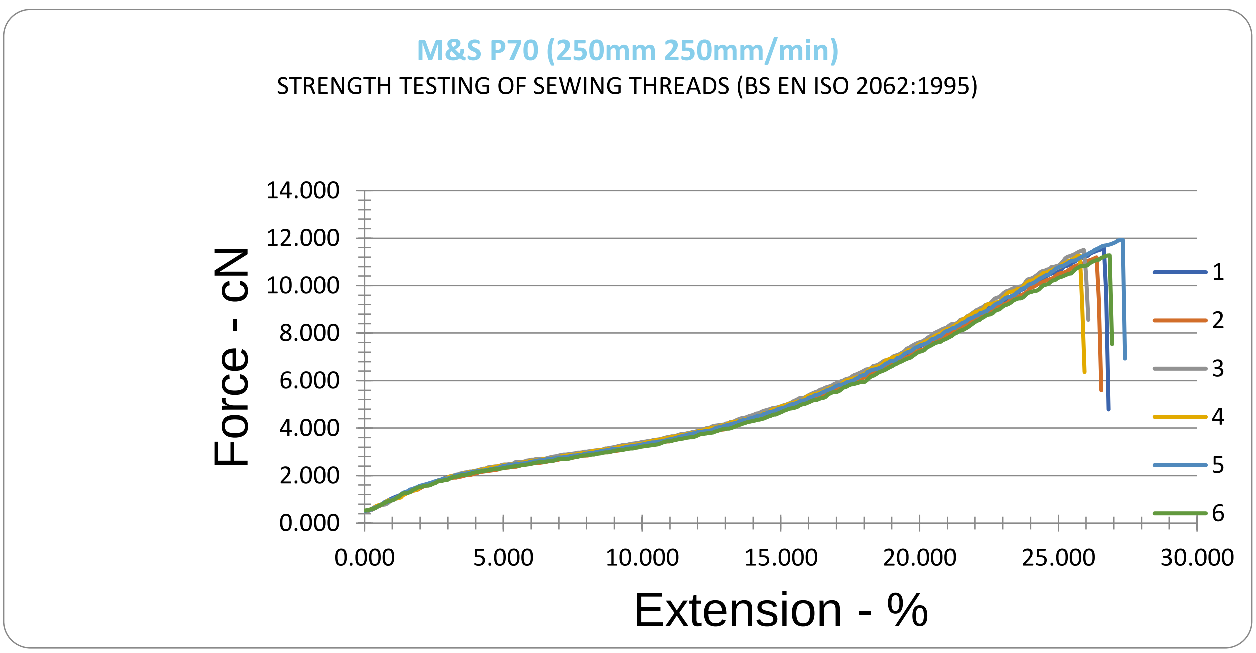

Figure 3.5: Sewing Thread Count of 100 Tex Strength and Elongation% Test

100 Tex linear density of sewing thread breaking load and elongation% shown in Figure 3.5. Where the graph shows that the total number of experiments was ten and breaking load between 10 cN/tex to 12 cN/tex and Sewing thread Elongation% was 26% to 28%.

Chapter 4

Experimental Results Analysis

In this study, we have used a dataset from the factory with the proposed 11 important features. Here we have an analysis of the various factors that directly or indirectly influenced the thread breakage. (i.e., Significant Sewing Thread Breakage: 1= positive, Not Thread Breakage 0=negative). For 11 functions, ANN (artificial neural network) accuracy is multilayer perceptron distribution accuracy, J48 decision tree, random forest, SMO (sequential minimal optimization) and 100% stochastic gradient descent (SGD) and performance. Better than other classes. ... Algorithms such as Voted Perceptron (99.80%), Naïve Bayes and Naïve Bayes Updated (94%), and logistic regression (98.40%). In Bangladesh, most companies are unaware of the impact of filament cutting and further processing on productivity.

Thereafter, we applied different data mining or supervised machine learning algorithms in the environment of WEKA 3.8 set to compare between different classifiers and different data sets. Also, we have applied 10-fold cross validation (70% of the data is used for training and 30% is used for testing) on the datasets. The classifiers name with various properties of classifiers described in Table 4.10.

The main reason for thread cutting is a lack of technology and inexperienced production-related works such as conventional technology and insufficient training facility of the industries. This intelligent automation system can predict the condition of the seam stitches by measuring some simple information that is useful to factory people. Finally, it will suggest the appropriate model for predict the breakage and improve productivity.

$$\textbf{Classification Accuracy}\ (\textbf{CA})\% = \frac{(\textbf{TP} + \textbf{TN})}{(\textbf{TP} + \textbf{TN} + \textbf{FP} + \textbf{FN})}\ \textbf{X 100}$$

$$\textbf{Error Rate}\ (\textbf{ER}) = \frac{(\textbf{FP} + \textbf{FN})}{(\textbf{TP} + \textbf{TN} + \textbf{FP} + \textbf{FN})}$$

$$\mathbf{Precision}\ \% = \frac{\mathbf{TP}}{(\mathbf{TP} + \mathbf{FP})}\ \mathbf{X\ 100}$$

$$\mathbf{Recall}\% = \frac{\mathbf{TP}}{(\mathbf{TP} + \mathbf{FN})}\ \mathbf{x\ 100}$$

Where,

TP - True Positive, FP - False Positive, FN -False Negative. TN- True Negative

Here, Positive means sewing Thread will not Breakage (NO) and Negative means Significant thread Breakage (Yes).

F1: This is a function of Precision and Recall. The F1 score is the harmonic mean of Precision and Recall

A confusion matrix is used to describe the performance of a classification model,

True Positive (TP): Cases when classifier predicted TRUE (Thread Will not Breakage) and class was TRUE (Sewing Thread was actually not Breakage).

True Negative (TN): Cases when classifier predicted FALSE (Thread Will Breakage) and class was FALSE (Sewing Thread was actually Breakage).

False Positive (FP): (Type – I Error): Classifier when predicted TRUE, but Correct class was FALSE (Sewing Thread actually significantly Breakage).

False Negative (FN): (Type – II Error): Classifier when predicted FALSE, but Correct class was TRUE (Sewing Thread actually will not Breakage).

Table 4.1: Result of J48 Decision Tree

Descriptions	Number of Instances	Percentages
Correctly Classified Instances	1000	100%
Incorrectly Classified Instances	0	0
Kappa statistic		1
Mean absolute error		0
Root mean squared error		0
Relative absolute error		0
Root relative squared error		0

Accuracy (Percentage) of Classes

TP (%)	FP (%)	Precision	Recall	F1	MCC	ROC	Class
100.00	0	100.00	100.00	100.00	100.00	100.00	0
100.00	0	100.00	100.00	100.00	100.00	100.00	1
100.00	**0**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**AVG.**

Confusion Matrix

Class	TP	FN
a = 0	351	0
	FP	**TN**
b = 1	0	649

Table 4.2: Results of Multilayer Perceptron

Descriptions	**Number of Instances**	**Percentages**
Correctly Classified Instances	1000	100
Incorrectly Classified Instances	0	0
Kappa statistic		1
Mean absolute error		0
Root mean squared error		0
Relative absolute error		0
Root relative squared error		0

Accuracy (Percentage) of Classes

TP %	FP %	Precision	Recall	F1	MCC	ROC	Class
100.00	0	100.00	100.00	100.00	100.00	100.00	0
100.00	0	100.00	100.00	100.00	100.00	100.00	1
100.00	**0**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**AVG.**

Confusion Matrix

Class	**TP**	**FN**
a = 0	351	0
	FP	**TN**
b = 1	0	649

Table 4.3: Results of Random Forest

Descriptions	Number of Instances	Percentages
Correctly Classified Instances	1000	100
Incorrectly Classified Instances	0	0
Kappa statistic		1
Mean absolute error		0
Root mean squared error		0
Relative absolute error		0
Root relative squared error		0

Accuracy (Percentage) of Classes

TP %	FP %	Precision	Recall	F1	MCC	ROC	Class
100.00	0	100.00	100.00	100.00	100.00	100.00	0
100.00	0	100.00	100.00	100.00	100.00	100.00	1
100.00	**0**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**AVG.**

Confusion Matrix

Class	TP	FN
a = 0	351	0
	FP	**TN**
b = 1	0	649

Table 4.4: Results of Stochastic Gradient Descent (SGD)

Descriptions	Number of Instances	Percentages
Correctly Classified Instances	1000	100
Incorrectly Classified Instances	0	0
Kappa statistic		1
Mean absolute error		0
Root mean squared error		0
Relative absolute error		0
Root relative squared error		0

Accuracy (Percentage) of Classes

TP (%)	FP (%)	Precision	Recall	F1	MCC	ROC	Class
100.00	0	100.00	100.00	100.00	100.00	100.00	0
100.00	0	100.00	100.00	100.00	100.00	100.00	1
100.00	**0**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**AVG.**

Confusion Matrix

Class	**TP**	**FN**
a = 0	351	0
	FP	**TN**
b = 1	0	649

Table 4.5: Results of Sequential Minimal Optimization (SMO)

Descriptions	**Number of Instances**	**Percentages**
Correctly Classified Instances	1000	100
Incorrectly Classified Instances	0	0
Kappa statistic		1
Mean absolute error		0
Root mean squared error		0
Relative absolute error		0
Root relative squared error		0

Accuracy (Percentage) of Classes

TP %	FP %	Precision	Recall	F1	MCC	ROC	Class
100.00	0	100.00	100.00	100.00	100.00	100.00	0
100.00	0	100.00	100.00	100.00	100.00	100.00	1
100.00	**0**	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**	**AVG.**

Confusion Matrix

Class	**TP**	**FN**
a = 0	351	0
	FP	**TN**
b = 1	0	649

Table 4.6: Result of Voted Perceptron

Descriptions	Number of Instances	Percentages
Correctly Classified Instances	998	99.8
Incorrectly Classified Instances	2	0.2
Kappa statistic		0.9956
Mean absolute error		0.002
Root mean squared error		0.0447
Relative absolute error		0.4389
Root relative squared error		9.3699

Accuracy (Percentage) of Classes

TP %	FP %	Precision	Recall	F1	MCC	ROC	Class
100.00	0.30	99.40	100.00	99.70	99.80	99.40	0
99.70	0.00	100.00	99.70	99.80	99.90	99.90	1
99.80	**0.10**	**99.80**	**99.80**	**99.60**	**99.90**	**99.80**	**AVG.**

Confusion Matrix

Class	TP	FN
a = 0	351	0
	FP	**TN**
b = 1	2	647

Table 4.7:Results of Logistic Regression

Descriptions	Number of Instances	Percentages
Correctly Classified Instances	984	98.4
Incorrectly Classified Instances	16	1.6
Kappa statistic		0.965
Mean absolute error		0.0166
Root mean squared error		0.0119
Relative absolute error		3.6404
Root relative squared error		24.9313

Accuracy (Percentage) of Classes

TP %	FP %	Precision	Recall	F1	MCC	ROC	Class
98.30	1.50	97.20	98.30	97.70	96.50	99.40	0
98.50	1.70	99.10	98.50	98.80	96.50	99.20	1
98.40	**1.60**	**98.40**	**98.40**	**98.40**	**96.50**	**99.30**	**AVG.**

Confusion Matrix

Class	TP	FN
a = 0	345	6
	FP	**TN**
b = 1	10	639

Table 4.8: Results of Naïve Bayes Algorithm

Descriptions	Number of Instances	Percentages
Correctly Classified Instances	940	94
Incorrectly Classified Instances	60	6
Kappa statistic		0.8686
Mean absolute error		0.0665
Root mean squared error		0.212
Relative absolute error		14.5953
Root relative squared error		44.4191

Accuracy (Percentage) of Classes

TP %	FP %	Precision	Recall	F1	MCC	ROC	Class
92.00	4.90	91.20	92.00	91.50	86.90	99.10	0
95.10	8.00	95.70	95.10	95.40	86.90	99.10	1
94.00	**6.90**	**94.00**	**94.00**	**94.00**	**86.90**	**99.10**	**AVG.**

Confusion Matrix

Class	TP	FN
a = 0	326	28
	FP	**TN**
b = 1	32	617

Table 4.9: Accuracy (%) of Various Methods of Machine Learning (10-Fold)

Algorithms of Machine learning	**Accuracy (%)**
Multilayer Perceptron	100.00
Logistic Regression	98.40
J48 Decision Tree	100.00
Naïve Bayes	94.00
Sequential Minimal Optimization (SMO)	100.00
Stochastic Gradient Descent	100.00
Random Forest	100.00
Voted Perceptron	99.80
Naïve Bayes Updated	94.00

Table 4.10: Performance Analysis of Various Supervised Methods using Machine Learning Technique

Algorithms	**Accuracy (%)**	**Precision**	**Recall**	**F -Measurement**
J48 Decision Tree	100.00	100.00	100.00	100.00
Logistic Regression	98.40	98.40	98.40	98.40
Multilayer Perceptron	100.00	100.00	100.00	100.00
Naïve Bayes	94.00	94.00	94.00	94.00
Random Forest	100.00	100.00	100.00	100.00
SGD	100.00	100.00	100.00	100.00
SMO	100.00	100.00	100.00	100.00
Voted Perceptron	99.80	99.80	99.80	99.80
Naïve Bayes Updated	94.00	94.00	94.00	94.00

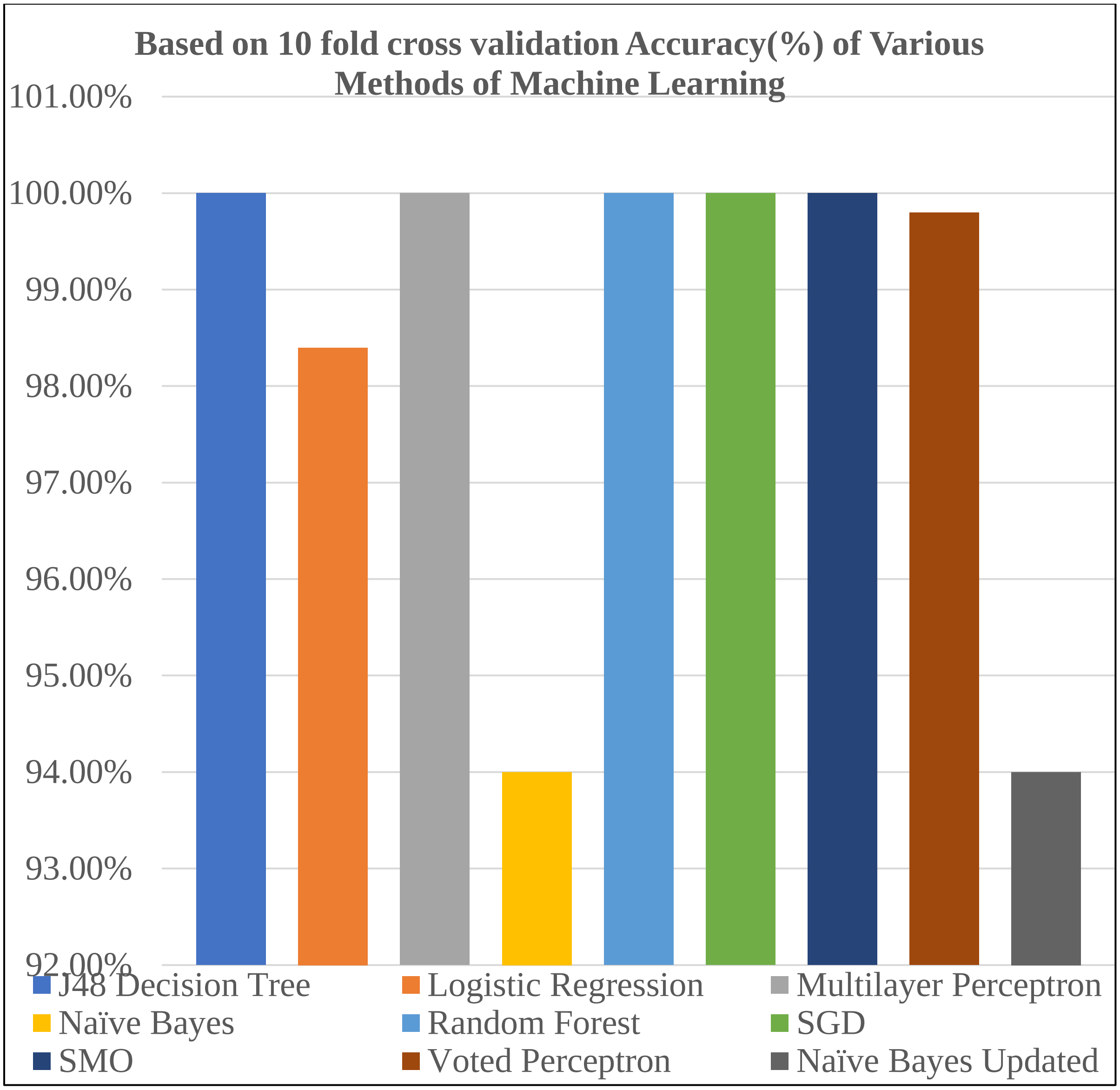

Figure 4.1: Performance of Various Supervised Methods by Machine Learning Technique

Figure-4.1, displayed 100% accuracy of Decision Tree(J48), Multilayer Perceptron, Random Forest, Sequential Minimal Optimization, and Stochastic Gradient Descent whereas 99.80% Voted Perceptron, 94% Naïve Bayes and Naïve Bayes Updated and 98.40% Logistic Regression.

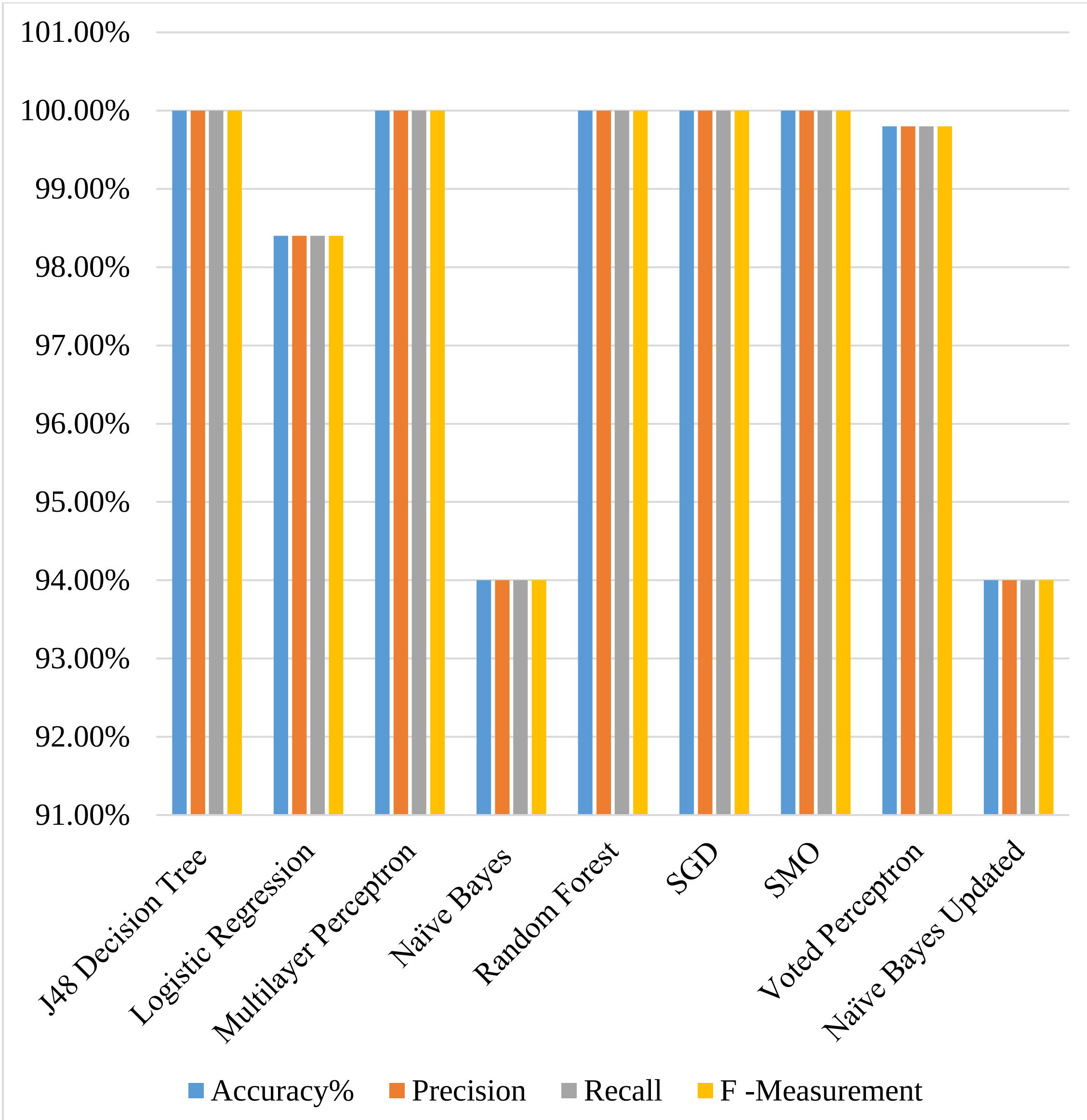

Figure 4.2: Performance of Various Machine Learning technique with 10-Fold Cross Validation

Figure-4.2 shown higher execution around 100% appeared in Decision Tree (J48), Multilayer Perceptron, Random Forest, Sequential Minimal Optimization (SMO), and Stochastic Gradient Descent (SGD) based on 10-fold cross-validation of the Precision, Accuracy, Review and F-Measurement rate of the distinctive calculations and comparatively, Voted Perceptron (99.80%), Naïve Bayes and Naïve Bayes Upgraded (94%), Calculated Relapse (98.40%).

Table 4.11: Accuracy Percentages of Various Classifiers

Accuracy (Percentages) of Various Classifiers									
Obs. No	Accuracy Percentages (Based on Cross-Validation Folds)								
	Classifier Name	10 Folds	50 Folds	100 Folds	250 Folds	500 Folds	750 Folds	1000 Folds	AVG:
1	Naïve Bayes	94.00	94.00	94.00	93.60	93.60	93.60	93.70	93.79
2	Naïve Bayes Updated	94.00	94.00	94.00	93.60	93.60	93.60	93.70	93.79
3	Random Forest Tree	100.00	100.00	99.90	99.90	99.80	99.80	99.90	99.90
4	Logistic Regression	98.40	99.90	99.90	100.00	99.90	99.80	99.80	99.67
5	Voted Perceptron	99.80	99.70	99.40	99.60	99.90	99.90	99.60	99.70
6	Multilayer Perceptron	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
7	SMO	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
8	SGD	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
9	J48	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00

SMO = Sequential Minimal Optimization, SGD = Stochastic Gradient Descent.

J48 = Decision Tree.

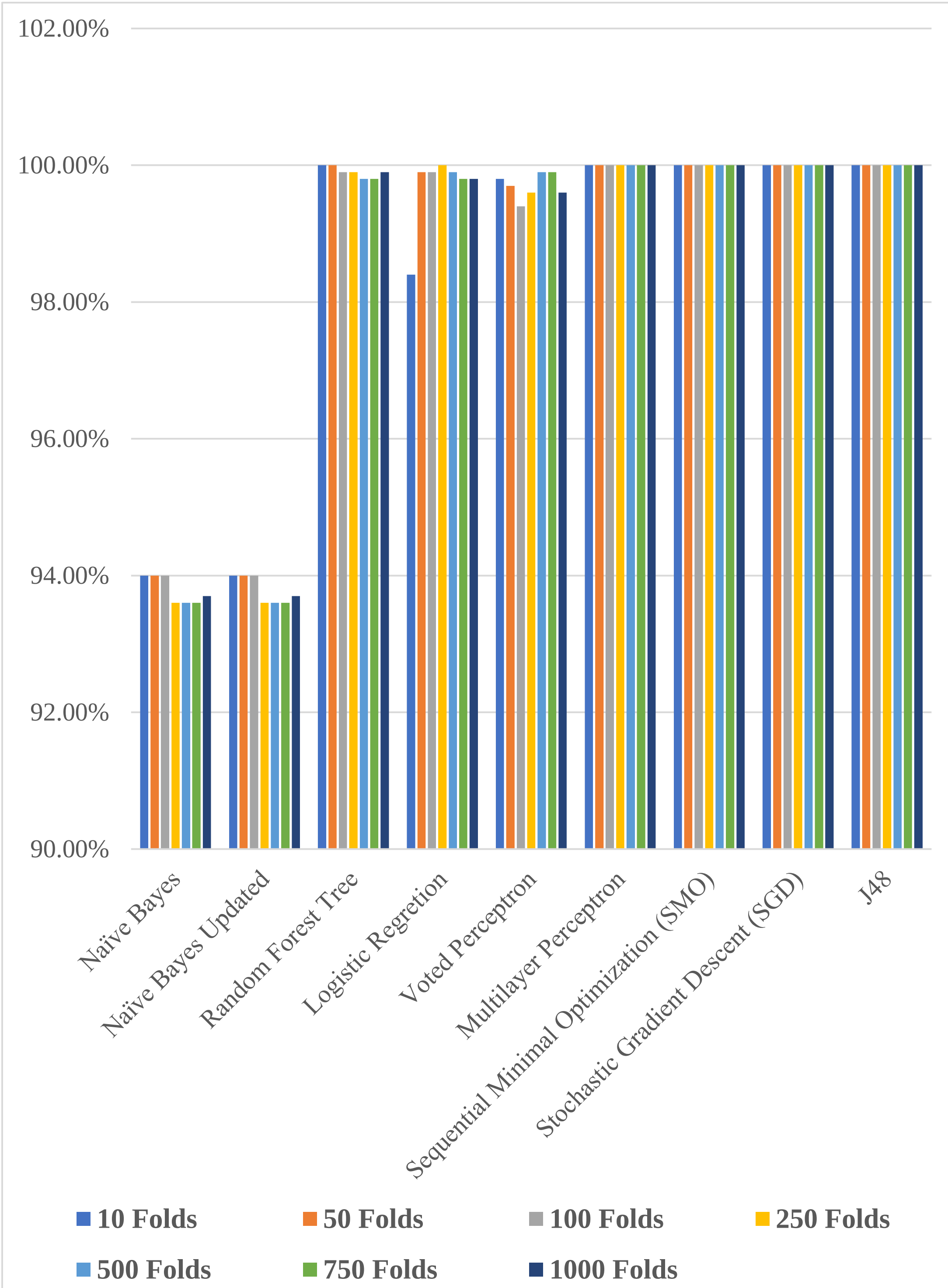

Figure 4.3: Accuracy (Percentage) of Different Cross-Validation Folds of Various. Classifiers

CHAPTER 5

Conclusion and Future Works

5.1 Summary

In this work, we collected data from the apparel industries in Bangladesh and developed a predictable model for cutting sewing threads to improve productivity in the garment industry. We selected 11 key thread cutting indicators and developed a predictive model containing 9 monitored machine learning algorithms. For 11 functions, ANN (artificial neural network) accuracy is multilayer perceptron distribution accuracy, J48 decision tree, random forest, SMO (sequential minimal optimization) and 100% stochastic gradient descent (SGD) and performance. Better than other classes. Algorithms such as Voted Perceptron (99.80%), Naïve Bayes and Naïve Bayes Updated (94%), and logistic regression (98.40%).

5.2 Discussion

In this research we have applied Eleven (11) features and nine (09) well known supervised machine learning algorithms and analyze the prediction accuracy percentages of sewing thread breakage. Previous most of the authors or researchers have discussed various machine learning algorithms in textile industries. The precision of ANN (Artificial Neural Network) multilayer perceptron classification, J48 Decision tree, Random Forest, Sequential Minimum Optimization (SMO), and Stochastic Gradient Descent (SGD) has been found to beat other classification calculations, similar to voted perceptron (upgraded 99.80%), Naive Bayesian and Updated Naive Bayesian (94%), calculated (98.40%). In Bangladesh, most companies are uninformed of the cost of thread cutting and re-process productivity. The most reason for sewing thread breakage may be a need for innovation and inexperienced production-related work. The automation system can predict the condition of the thread and measuring a few featured factors that can analysand make predictions of the effect. Ultimately, this model will support production quality and increase profitability across industries and economies.

5.3 Limitations

From the research work, we could not focus on a few impediments and did not consider the following:

- It is not possible to collect large amounts of data.
- We have not investigated the various brands of oils used in sewing needles.
- When it comes to sewing, I couldn't think of manpower skills.
- The thread breaks down and sewing machine speed cannot be compared with worldwide standards.

5.4 Future work

Finally, we will suggest for future work on the three things:

- Prepares database repository for sewing thread cutting based on Bangladesh garment industry data.
- Prepare a standard automatic data acquisition system.
- Development of a mobile data collection system through the Internet.

5.5 Conclusion

The whole purpose of our work is to more accurately predict sewing thread cuts and create our own dataset. This will be the first data warehouse for sewing thread cutting in Bangladesh. So, we have collected sewing data from six garment industries in Bangladesh. It is based on different categories such as knitting, weaving and denim. Of the 11 features identified in 1000 data samples, a total of 35 sewing production lines were used to document sewing thread cutting. According to the accuracy% of classification artificial neural network (ANN), multilayer perceptron distribution, decision tree J48, random forest, sequential minimum optimization and SGD (probability gradient descent) was analyzed to be 100%, and surpasses other algorithm distributions. Perceptron voting (99.80%), updated naive Bayesian and Bayesian (94%), logistic regression accuracy (98.40%), and more.

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Appendix A

M&S P70 (250mm 250mm/min)

STRENGTH TESTING OF SEWING THREADS (BS EN ISO 2062:1995)

Test Details

Test Name:	Tensile Strength (black)	Date:	1/19/2020
Specimens:	10	Load Cell SN:	SERIAL NUMBER
Required Directions:	-	Version:	5.0.18.0
Jaw Scheme:	T27	Firmware:	V2.8
Jaw Separation:	250.00 mm	Titan SN:	1410/15/1017
Force Control Gain:	25	Tested by:	Abu Hanif
Load Cell:	100 N		

Procedure Settings

Break Detection:	20 %
Pretension (Linear Density)	
Linear Density:	50.00 tex
Pretension:	0.50 cN/tex
Pull To Load Cell Maximum	
Speed:	250.00 mm/min

Results

Specimen	Max Force (cN)	Max. Tenacity (cN/tex)	Extension (%)
1	441.92	8.84	21.56
2	480.73	9.61	21.77
3	485.73	9.71	22.57
4	518.97	10.38	23.68
5	487.87	9.76	22.70
6	466.79	9.34	22.96
7	479.29	9.59	22.88
8	415.52	8.31	21.17
9	463.84	9.28	23.96
10	499.02	9.98	22.90
Mean	473.97	9.48	22.61
Coeff Of Var	6.15%	6.15%	3.94%

Figure 0.1: Sewing Thread Tensile Strength Test Report

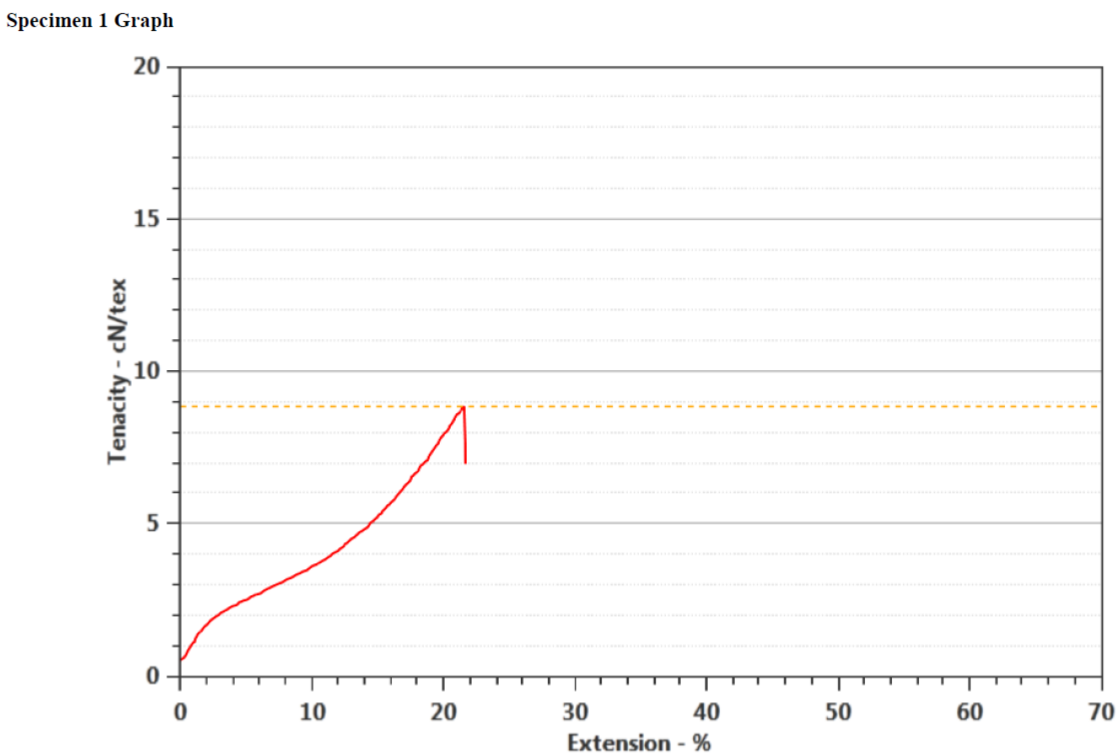

Figure 0.2: Sewing thread Count of 60 Tex Tenacity and Extension%

Specimen 2 Graph

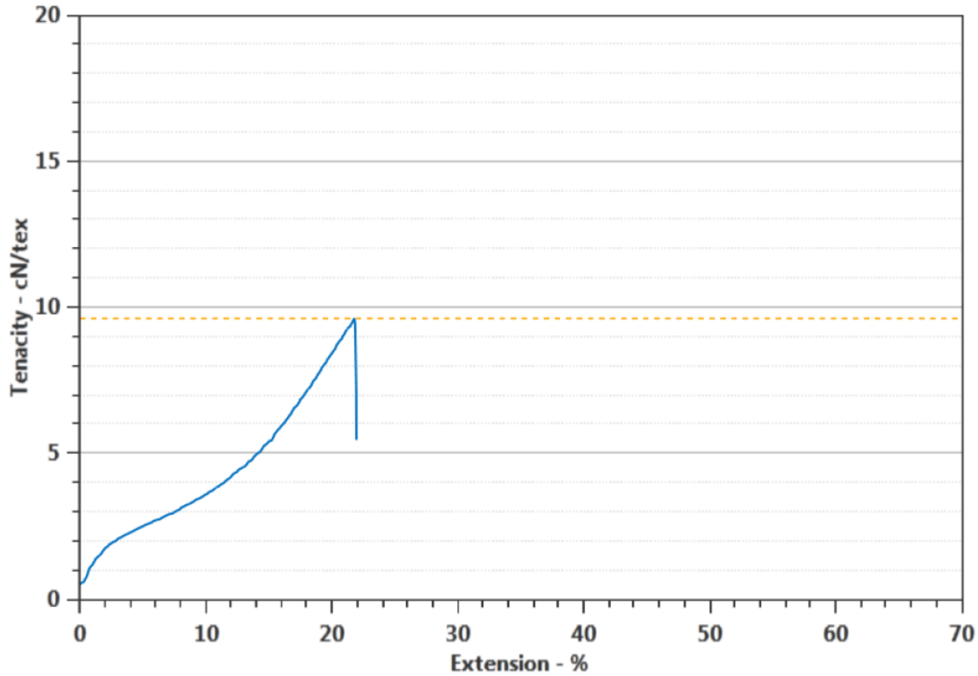

Figure 0.3: Sewing thread Count of 60 Tex Tenacity and Extension%

Specimen 4 Graph

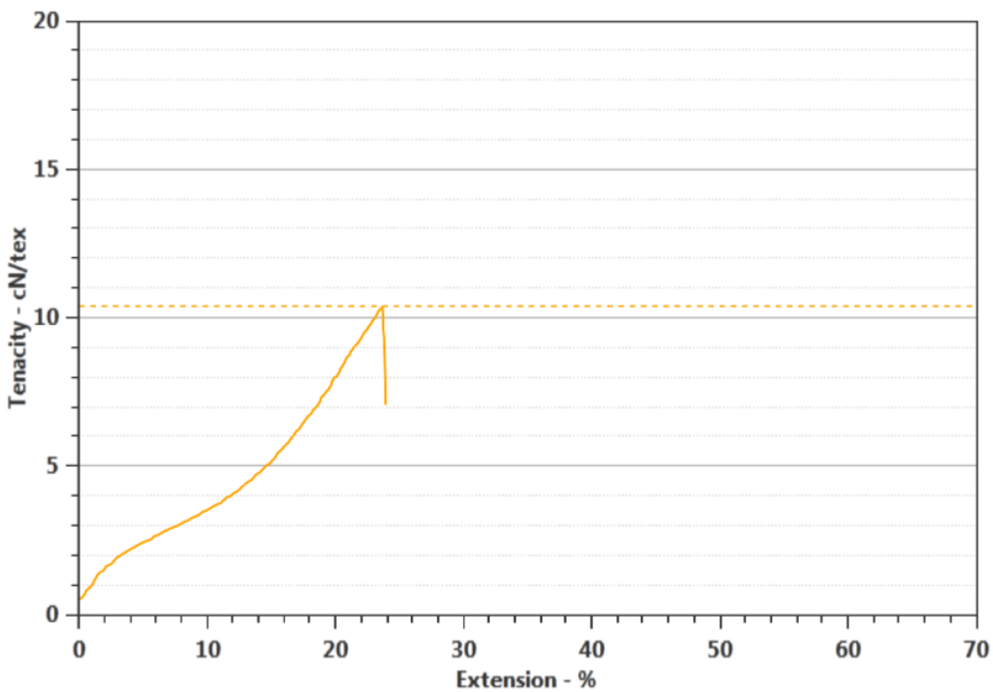

Figure 0.4: Sewing thread Count of 60 Tex Tenacity and Extension %

Table 0.1: Research Data

Fabric Name	ST	MS	SPI	NN	FT	GSM	T_S	Tex	El	No of B._hr
Jersey	5	3500	10	9	0.18	160	4.75	30	15	2
Jersey	6	3800	10	9	0.21	160	5.15	30	15	3
Jersey	5	3600	10	9	0.22	160	5.15	30	15	1
Jersey	4	3500	10	9	0.22	160	5.15	30	17	1
Jersey	5	3500	10	9	0.21	160	5.15	30	15	1
Jersey	6	3800	10	9	0.21	160	5.15	30	15	2
Jersey	5	3600	10	9	0.21	162	4.9	30	15	2
Jersey	4	3500	10	9	0.21	160	5.15	30	15	3
Jersey	5	3800	10	9	0.21	160	5.15	30	15	2
Jersey	5	3800	10	9	0.2	160	5.15	30	15	2
Jersey	5	3500	10	9	0.19	160	4.5	30	15	2
Jersey	6	3800	10	9	0.21	160	5.15	30	13	3
Jersey	5	3600	10	9	0.21	160	4.85	30	15	2
Jersey	4	3500	10	9	0.22	160	5.2	30	15	2
Jersey	5	3800	10	9	0.24	160	5.15	30	15	2
Jersey	5	3500	10	9	0.2	160	5.15	30	15	1
Jersey	6	3800	10	9	0.21	160	5.15	30	14	3
Jersey	5	3600	10	9	0.21	164	4.2	30	15	3
Jersey	4	3500	10	9	0.24	160	5.58	30	15	1
Jersey	5	3800	10	9	0.6	160	5.15	30	15	2
Jersey	5	3500	10	9	0.21	160	5.25	30	15	1
Jersey	5	3500	8	9	0.22	180	4.65	30	15	2
Jersey	6	3800	8	9	0.22	180	4.11	30	14	3
Jersey	5	3600	8	9	0.22	180	4.11	30	15	1
Jersey	4	3500	8	9	0.22	180	5.10	30	17	0

Table 0.2: Research Data

Fabric Name	ST	MS	SPI	NN	FT	GSM	T_S	Tex	El	No of B._hr
DLacoste	6	3600	10	10	0.28	220	7.41	60	14	3
DLacoste	5	3500	10	10	0.30	220	7.41	60	13	3
DLacoste	4	3000	10	10	0.28	220	7.5	60	15	1
DLacoste	5	3200	10	10	0.28	220	7.41	60	14	3
DLacoste	4	3500	10	10	0.28	220	7.41	60	14	2
DLacoste	6	3600	10	10	0.29	220	7.41	60	14	2
DLacoste	5	3500	10	10	0.28	224	7.41	60	13	1
DLacoste	4	3000	10	10	0.28	220	7.41	60	15	3
DLacoste	5	3200	10	10	0.29	222	7.41	60	14	2
DLacoste	4	3500	10	10	0.25	220	7.41	60	14	1
DLacoste	6	3600	10	10	0.28	224	7.41	60	14	1
DLacoste	5	3500	10	10	0.28	220	7.35	60	13	2
DLacoste	4	3000	10	10	0.28	220	7.45	60	15	3
DLacoste	5	3200	10	10	0.28	220	7.4	60	14	2
DLacoste	4	3500	10	10	0.26	220	7.41	60	15	0
DLacoste	6	3600	10	10	0.32	220	7.41	60	14	2
DLacoste	5	3500	10	10	0.28	220	7.41	60	13	3
DLacoste	4	3000	10	10	0.29	220	7.55	60	15	1
DLacoste	5	3200	10	10	0.28	220	7.41	60	15	3
DLacoste	4	3500	10	10	0.27	220	7.41	60	15	2
DLacoste	6	3600	10	10	0.31	220	7.41	60	14	2
DLacoste	5	3500	10	10	0.28	220	7.41	60	13	2
DLacoste	4	3000	10	10	0.28	220	7.48	60	15	3
DLacoste	5	3200	10	10	0.30	220	7.41	60	14	2
DLacoste	4	3500	10	10	0.24	220	7.41	60	14	3

Table 0.3: Research Data

Fabric Name	ST	MS	SPI	NN	FT	GSM	T_S	Tex	El	No of B._hr
Fleece	6	3600	10	10	0.56	310	8.5	60	15	3
Fleece	5	3500	10	10	0.56	310	8.5	60	15	3
Fleece	4	3000	10	10	0.56	310	8.5	60	17	1
Fleece	5	3200	10	10	0.56	310	8.5	60	15	3
Fleece	4	3500	10	10	0.57	312	8.5	60	16	2
Fleece	6	3600	10	10	0.58	310	8.5	60	15	3
Fleece	5	3500	10	10	0.55	310	8.5	60	16	2
Fleece	4	3000	10	10	0.57	314	8.5	60	17	1
Fleece	5	3200	10	10	0.54	310	8.5	60	17	1
Fleece	4	3500	10	10	0.57	316	8.5	60	15	3
Fleece	6	3600	10	10	0.54	310	8.5	60	16	2
Fleece	5	3500	10	10	0.54	310	8.5	60	17	1
Fleece	4	3000	10	10	0.58	310	8.5	60	16	3
Fleece	5	3200	10	10	0.58	310	8.5	60	16	2
Fleece	4	3500	10	10	0.58	310	8.5	60	17	1
Fleece	6	3600	10	10	0.56	312	8.5	60	16	2
Fleece	5	3500	10	10	0.58	312	8.5	60	17	1
Fleece	4	3000	10	10	0.58	310	8.5	60	17	0
Fleece	5	3200	10	10	0.57	310	8.5	60	16	2
Fleece	4	3500	10	10	0.61	312	8.5	60	17	1
Fleece	6	3600	10	10	0.56	314	8.5	60	15	3
Fleece	5	3500	10	10	0.52	310	8.5	60	16	2
Fleece	4	3000	10	10	0.61	314	8.5	60	17	0
Fleece	5	3200	10	10	0.55	310	8.5	60	17	1
Fleece	4	3500	10	10	0.61	316	8.5	60	16	1

Table 0.4: Research Data

Fabric Name	ST	MS	SPI	NN	FT	GSM	T_S	Tex	El	No of B._hr
Lacoste	6	3600	10	10	0.28	220	7.41	60	14	3
Lacoste	5	3500	10	10	0.28	220	7.41	60	13	2
Lacoste	4	3000	10	10	0.28	220	7.41	60	15	1
Lacoste	5	3200	10	10	0.28	224	7.42	60	14	2
Lacoste	4	3500	10	10	0.28	220	7.41	60	14	1
Lacoste	6	3600	10	10	0.28	220	7.41	60	14	2
Lacoste	5	3500	10	10	0.28	222	7.41	60	14	1
Lacoste	4	3000	10	10	0.28	220	7.41	60	13	3
Lacoste	5	3200	10	10	0.28	220	7.35	60	14	3
Lacoste	4	3500	10	10	0.28	220	7.41	60	14	2
Lacoste	6	3600	10	10	0.28	222	7.44	60	14	2
Lacoste	5	3500	10	10	0.28	220	7.4	60	14	1
Lacoste	4	3000	10	10	0.28	220	7.41	60	15	2
Lacoste	5	3200	10	10	0.28	220	7.41	60	14	3
Lacoste	4	3500	10	10	0.28	220	7.41	60	14	3
Lacoste	6	3600	10	10	0.28	220	7.41	60	14	1
Lacoste	5	3500	10	10	0.26	220	7.44	60	13	2
Lacoste	4	3000	10	10	0.28	220	7.5	60	14	3
Lacoste	5	3200	10	10	0.28	220	7.36	60	14	3
Lacoste	4	3500	10	10	0.28	220	7.41	60	14	0
Lacoste	6	3600	10	10	0.28	220	7.41	60	13	4
Lacoste	5	3500	10	10	0.28	224	7.42	60	15	1
Lacoste	4	3000	10	10	0.28	220	7.55	60	15	3

Table 0.5: Research Data

Fabric Name	ST	MS	SPI	NN	FT	GSM	T_S	Tex	El	No of B._hr
Fleece	6	3600	10	10	0.56	310	8.5	60	15	3
Fleece	5	3500	10	10	0.56	310	8.5	60	15	3
Fleece	4	3000	10	10	0.56	310	8.5	60	17	1
Fleece	5	3200	10	10	0.56	310	8.5	60	15	3
Fleece	4	3500	10	10	0.57	312	8.5	60	16	2
Fleece	6	3600	10	10	0.58	310	8.5	60	15	3
Fleece	5	3500	10	10	0.55	310	8.5	60	16	2
Fleece	4	3000	10	10	0.57	314	8.5	60	17	1
Fleece	5	3200	10	10	0.54	310	8.5	60	17	1
Fleece	4	3500	10	10	0.57	316	8.5	60	15	3
Fleece	6	3600	10	10	0.54	310	8.5	60	16	2
Fleece	5	3500	10	10	0.54	310	8.5	60	17	1
Fleece	4	3000	10	10	0.58	310	8.5	60	16	3
Fleece	5	3200	10	10	0.58	310	8.5	60	16	2
Fleece	4	3500	10	10	0.58	310	8.5	60	17	1
Fleece	6	3600	10	10	0.56	312	8.5	60	16	2
Fleece	5	3500	10	10	0.58	312	8.5	60	17	1
Fleece	4	3000	10	10	0.58	310	8.5	60	17	0
Fleece	5	3200	10	10	0.57	310	8.5	60	16	2
Fleece	4	3500	10	10	0.61	312	8.5	60	17	1
Fleece	6	3600	10	10	0.56	314	8.5	60	15	3
Fleece	5	3500	10	10	0.52	310	8.5	60	16	2
Fleece	4	3000	10	10	0.61	314	8.5	60	17	0
Fleece	5	3200	10	10	0.55	310	8.5	60	17	1

Table 0.6: Research Data

Fabric Name	ST	MS	SPI	NN	FT	GSM	T_S	Tex	El	No of B._hr
Pique	6	3600	10	10	0.3	220	8.5	60	14	3
Pique	5	3500	10	10	0.3	220	8.54	60	17	2
Pique	4	3000	10	10	0.3	220	8.5	60	17	1
Pique	5	3200	10	10	0.3	220	8.5	60	17	2
Pique	4	3500	10	10	0.8	220	8.5	60	17	1
Pique	6	3600	10	10	0.3	222	8.5	60	16	2
Pique	5	3500	10	10	0.3	220	8.5	60	17	1
Pique	4	3000	10	10	0.3	220	8.5	60	17	3
Pique	5	3200	10	10	0.3	220	8.5	60	13	3
Pique	4	3500	10	10	0.3	220	8.5	60	17	2
Pique	6	3600	10	10	0.3	224	8.5	60	13	3
Pique	5	3500	10	10	0.3	220	8.57	60	17	1
Pique	4	3000	10	10	0.3	220	8.5	60	17	2
Pique	5	3200	10	10	0.3	220	8.5	60	16	1
Pique	4	3500	10	10	0.3	222	8.5	60	17	1
Pique	6	3600	10	10	0.3	226	8.5	60	14	3
Pique	5	3500	10	10	0.3	220	8.56	60	17	2
Pique	4	3000	10	10	0.3	220	8.65	60	17	1
Pique	5	3200	10	10	0.3	220	8.5	60	15	2
Pique	4	3500	10	10	0.3	220	8.5	60	17	0
Pique	6	3600	10	10	0.3	220	8.54	60	16	2
Pique	5	3500	10	10	0.3	220	8.58	60	17	2
Pique	4	3000	10	10	0.3	220	8.6	60	17	1
Pique	5	3200	10	10	0.3	220	8.5	60	14	2

Table 0.7: Research Data

Fabric Name	ST	MS	SPI	NN	FT	GSM	T_S	Tex	El	No of B._hr
RDenim	5	3000	12	14	0.56	280	8.75	50	22	3
RDenim	6	2800	12	14	0.56	280	9.48	50	22.61	1
RDenim	5	2400	12	14	0.56	280	9.48	50	22.61	1
RDenim	7	2800	12	14	0.56	280	9.25	50	20	3
RDenim	5	2500	12	14	0.56	280	10	50	22.61	0
RDenim	5	3000	12	14	0.56	280	9.48	50	22.61	1
RDenim	6	2800	12	14	0.56	278	9.41	50	22.61	3
RDenim	5	2400	12	14	0.56	280	9.49	50	24	0
RDenim	7	2800	12	14	0.56	280	9.48	50	22.61	1
RDenim	5	2500	12	14	0.56	280	10.1	50	22.61	0
RDenim	5	3000	12	14	0.56	280	9.5	50	22.61	1
RDenim	6	2800	12	14	0.56	176	9.42	50	22.61	1
RDenim	5	2400	12	14	0.56	280	9.47	50	22.61	1
RDenim	7	2800	12	14	0.56	280	9.48	50	22.54	1
RDenim	5	2500	12	14	0.56	280	9.48	50	22.12	1
RDenim	5	3000	12	14	0.56	280	9.52	50	22.61	1
RDenim	6	2800	12	14	0.56	277	9.4	50	22.61	1
RDenim	5	2400	12	14	0.56	280	9.46	50	22.61	1
RDenim	7	2800	12	14	0.56	280	9.15	50	20.15	3
RDenim	5	2500	12	14	0.56	280	10.1	50	22.61	0
RDenim	5	3000	12	14	0.56	280	8.8	50	20	3
RDenim	6	2800	12	14	0.56	276	9.35	50	22.61	1
RDenim	5	2400	12	14	0.56	280	9.5	50	22.61	0
RDenim	7	2800	12	14	0.56	280	9.48	50	22.52	1
RDenim	5	2500	12	14	0.56	280	9.48	50	22.23	1

Table 0.8: Research Data

Fabric Name	ST	MS	SPI	NN	FT	GSM	T_S	Tex	El	No of B._hr
SDenim	6	4000	10	16	0.62	310	12.2	100	26.48	1
SDenim	5	3800	10	16	0.62	310	9.15	100	26.25	3
SDenim	7	3800	10	16	0.62	310	11.5	100	23.12	1
SDenim	5	3600	10	16	0.62	310	9.54	100	26.48	3
SDenim	4	3600	10	16	0.62	310	11.5	100	25.25	1
SDenim	6	4000	10	16	0.62	310	10.5	100	24.15	3
SDenim	5	3800	10	16	0.62	310	11.5	100	26.48	1
SDenim	7	3800	10	16	0.62	310	12.2	100	22.15	3
SDenim	5	3600	10	16	0.62	310	8.65	100	26.48	4
SDenim	4	3600	10	16	0.62	310	11.5	100	25.26	1
SDenim	6	4000	10	16	0.62	310	8.75	100	23	5
SDenim	5	3800	10	16	0.62	310	10.2	100	26.48	3
SDenim	7	3800	10	16	0.62	310	10.5	100	24.25	4
SDenim	5	3600	10	16	0.62	310	8.78	100	26.48	4
SDenim	4	3600	10	16	0.62	310	11.5	100	25.45	1
SDenim	6	4000	10	16	0.62	310	10.6	100	24.25	3
SDenim	5	3800	10	16	0.62	310	10.2	100	26.48	3
SDenim	7	3800	10	16	0.62	310	8.25	100	22.25	5
SDenim	5	3600	10	16	0.62	310	11.5	100	26.48	1
SDenim	4	3600	10	16	0.62	310	11.5	100	25.46	0
SDenim	6	4000	10	16	0.62	310	12.2	100	26.48	1
SDenim	5	3800	10	16	0.62	310	10.3	100	26.48	3
SDenim	7	3800	10	16	0.62	310	12.1	100	22.14	3
SDenim	5	3600	10	16	0.62	310	11.5	100	26.48	3

Table 0.9: research Data

Fabric Name	ST	MS	SPI	NN	FT	GSM	T_S	Tex	El	No of B._hr
Twill	5	3800	10	14	0.3	260	8.05	40	11	2
Twill	7	3800	10	14	0.27	260	7.45	40	11	4
Twill	5	3600	10	14	0.27	260	7.8	40	10	3
Twill	4	3600	10	14	0.26	264	8.05	40	10	2
Twill	6	4000	10	14	0.27	220	10.1	60	14	4
Twill	5	3800	10	14	0.27	266	10.2	60	13	3
Twill	7	3800	10	14	0.27	220	10.1	60	15	3
Twill	5	3600	10	14	0.27	220	9.8	60	14	3
Twill	4	3600	10	14	0.27	268	10.1	60	14	3
Twill	6	4000	10	14	0.27	222	10.1	60	10	4
Twill	5	3800	10	14	0.27	220	10.2	60	11	3
Twill	4	3800	10	14	0.27	220	10.1	60	11	1
Twill	5	3600	10	14	0.27	220	9.78	60	10	3
Twill	7	3600	10	14	0.26	220	10.1	60	10	4
Twill	6	4000	10	14	0.27	224	10.1	60	10	4
Twill	5	3800	10	14	0.27	220	10.8	60	13	1
Twill	4	3800	10	14	0.27	222	10.1	60	11	3
Twill	5	3600	10	14	0.27	220	11.1	60	12	1
Twill	7	3600	10	14	0.27	224	10.1	60	10	3
Twill	6	4000	10	14	0.27	226	10.1	60	10	4
Twill	5	3800	10	14	0.27	220	10.8	60	14	1
Twill	4	3800	10	14	0.27	224	10.1	60	11	3
Twill	5	3600	10	14	0.27	220	11.2	60	13	1