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MACHINE LEARNING ALGORITHMS IN QUALITY CONTROL OF TEXTILE FIBER MANUFACTURING

MIROSLAV TRANKOV[1], EMIL HADZHIKOLEV[2], STANKA HADZHIKOLEVA[3]
University of Plovdiv Paisii Hilendarski, Plovdiv, Bulgaria
E-mail: [1]trankov86@gmail.com, [2]hadjikolev@uni-plovdiv.bg, [3]stankah@uni-plovdiv.bg

ABSTRACT

The paper presents a study on the use of machine learning methods in performing quality control in the production of textile fabrics. The main objectives, problems and parameters in yarn quality control are discussed. The results of using the Linear Regression, Logistic Regression, Decision Tree and Random Forest machine learning algorithms on production data for various yarn parameters are presented. Based on production data for 20 days, possible deviations from the research parameters for the 21st day are predicted. The approach used can also be applied for other aspects of the production process - to optimize planning, analyze the performance of different machines, analyze the raw materials used, identify poorly performing system components, etc.

Keywords: *Machine Learning, Textile Manufacturing, Textile Fiber Manufacturing, Yarn Quality*

1. INTRODUCTION

In the rapidly evolving field of textile fiber manufacturing, ensuring consistent quality is a significant challenge. Traditional quality control methods often struggle with the complexity and variability inherent in textile production. This study addresses the gap in effectively utilizing machine learning algorithms to enhance quality control processes in textile fiber manufacturing. We aim to explore how these advanced technologies can provide more accurate, efficient, and cost-effective solutions compared to conventional methods.

The main research questions are:

1. How can machine learning algorithms improve the accuracy and efficiency of quality control in textile fiber manufacturing?
2. What are the specific challenges in applying machine learning to textile quality control, and how can these be effectively addressed?
3. In what ways does the implementation of machine learning in this field compare to traditional quality control methods in terms of performance and cost-effectiveness?

Spinning mill managers have always been faced with the difficult task of achieving the best possible balance between yarn quality and production process efficiency. Problem situations leading to significant production and financial losses are: premature and unnecessary stoppage of work with minor changes in yarn quality; the phased or simultaneous shutdown of multiple machines that cannot be set up in a timely manner, the need for unplanned repairs, etc. Determining the exact moment for setting up and repairing each of the machines makes it possible to comprehensively plan the service activities, minimize the time for their implementation and optimize the work process.

In today's textile factories, modern autonomous machines are used, which continuously generate a huge flow of data about various characteristics of the yarn and the production process. At the same time, manual tracking of yarn quality or manual processing of generated data is inefficient and sometimes even impossible.

There are complete Enterprise solutions that provide additional specialized services in the quality control of yarn production. However, they are often expensive to integrate and difficult to maintain by the end user [1]. An alternative solution is the use of artificial intelligence, and in particular machine learning algorithms, to be used to process the data stream and predict various problems with the quality of the yarn being produced. Such techniques are increasingly used in industry both for total quality assurance [2], [3] and for various aspects of production, e.g. for predicting yarn breaks in textile fabrics [1]. An advantage of this type of model is finding patterns in the occurrence of manufacturing anomalies and predicting potential problems in the quality of the final product [4]. A number of open source libraries facilitate the development of predictive models for processes and events [5].

The article presents a study on the use of machine learning methods in the implementation of quality control in the production of textile fibers. The main objectives, problems and parameters in yarn quality control are discussed. The results of using the Linear Regression, Logistic Regression, Decision Tree, Random Forest machine learning algorithms and on production data for various yarn parameters are presented.

2. QUALITY CONTROL IN THE PRODUCTION OF TEXTILE FIBERS

Thread making is a complex technological process involving various production stages. Each of them tracks a number of specific quality criteria related to different defects.

2.1 Types of defects in the production of worsted yarns

Common defects of wool as a raw material, as well as problems arising in the manufacture of fibers, are as follows [6]:

1. Slubs – bold sections.
2. Cracker - short coils in places in the yarn. When the yarn is taut, the coil sometimes makes a popping sound.
3. Thick and thin places in the fiber.
4. The shaggy yarn.
5. Low yarn strength.
6. Poor braiding of threads.
7. Presence of external impurities. This includes synthetic foreign matter on the surface, regardless of yarn thickness, as well as colored foreign matter in white and dyed yarn.

In the textile industry, there are different methods and systems for classifying yarn defects, depending on the needs of manufacturers and end users.

Uster Statistics is a standard yarn quality evaluation method developed by the company Uster Technologies [7]. It is considered a global standard in the textile industry and measures various parameters such as yarn unevenness, knots, thin and thick places, etc. Uster Statistics offers comparative data from different manufacturers, enabling textile mills to assess the quality of their products against global standards. The standard uses statistical methods to analyze data, which helps manufacturers identify problems in the production process and take corrective action.

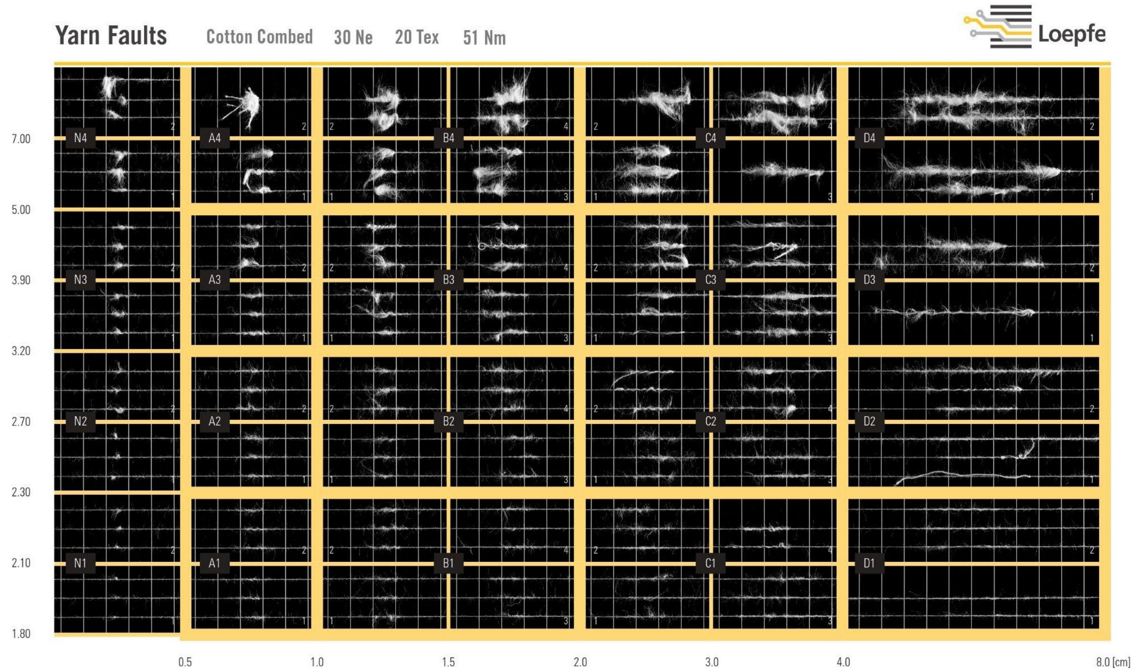

Figure 1. Loepfe categorization of yarn defects

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Another classification is proposed by Loepfe, a company specializing in quality control of textile yarns [8]. It is known for its innovative solutions for detecting and classifying defects in textile yarns. Loepfe generally divides defects into several main categories, which include: Thin and thick spots, Knots and knots, Foreign fibers and materials, Irregularities in structure, Color mismatches, and more. The classification may include additional parameters and subcategories that focus on specific aspects of yarn quality, such as defect length, frequency of occurrence, etc. Some of the Loepfe defects are presented in figure 1.

The two companies - Uster Technologies and Loepfe offer various electronic yarn cleaning devices that are used in the textile industry. Such are e.g. YarnMaster ZENIT and Uster Quantum. Moreover, the availability of data generated during operation of these devices makes it possible to evaluate their effectiveness [9].

There are numerous ISO standards that relate to the textile industry, including the quality of textile yarns. They cover various aspects such as physical characteristics, measurement methods, terminology, etc. Such are e.g. ISO 2060, ISO 2061, ISO 2062 for staple fiber yarns, ISO 5079 for textile fibers, ISO 11505 for yarns and threads, etc. [10]. The American Society for Testing and Materials (ASTM) [11] also offers various standards that are applicable to the evaluation of various aspects of textile materials and yarns. These may include tests for durability, elasticity, color fastness, etc. [ASTM]. Similarly, the International Wool Textile Organization develops standards that are primarily used to assess the quality of woolen yarns [12].

2.2 Quality control in the production of worsted yarns

The key characteristics determining efficiency in fiber production are interrelated: good end product quality achieved with high machine performance. The main objectives of quality control are the following:

1. Optimization of production resources - effective quality control helps reduce inefficiencies in the use of resources, resulting in higher productivity.
2. Cost control – detection of defects and defects at an early stage can significantly reduce the final cost of production.
3. Improvement and innovation - systematic quality control can stimulate ideas for process improvement and innovation to add value to the product.
4. Reduction of waste - producers can identify problems that lead to scrap and waste at an early stage.

A major problem in the production process is inefficient maintenance of the weaving machines. It often results in unplanned delays or shutdowns due to the need for machine adjustments. Employing a wide range of personnel to service the machines is expensive and not efficient enough because problems are often discovered too late after they have occurred. A solution is needed that predicts problems before they occur. For this purpose, various methods of artificial intelligence can be used, incl. different machine learning algorithms.

3. MACHINE LEARNING ALGORITHMS APPLYING

Machine learning algorithms can be used to optimize the textile fiber manufacturing process in various aspects, e.g.:

1. Predicting equipment failures and shutdowns – it is possible to analyze machine performance and predict potential failures, allowing maintenance to be planned before problems occur.
2. Resource optimization – machine learning algorithms can be used to analyze production data for materials, energy and time used, and develop optimizations that reduce costs and increase efficiency.
3. Adaptation of production processes - algorithms can optimize production parameters in real time, adapting them to the specific conditions in production, e.g. depending on changes in input materials, changes in room temperature and humidity, etc.

The use of machine learning algorithms for quality assurance in the worsted yarn manufacturing process involves the following main steps.

1. Acquaintance with the peculiarities of the production process, the equipment and technologies used, and the limitations caused by the technological specifications.
2. Collecting and aggregating production data and preparing it for subsequent use by machine learning algorithms.
3. Determining the significant characteristics of production data.
4. Fine-tuning the model and predicting possible problems in the quality of the produced batch.

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3.1. Manufacturing process

When familiarizing with the specifics of the manufacturing process and the limitations posed by the technological specifications, it is necessary to determine the main goals and applications of the predictive model to be developed. Most spinning machines in modern industry provide in real time the entire data set, incl. for a wide range of defects grouped by category, such as presented in fig. 1.

Quality control systems store historical production data for items and customer orders, which provides a good basis for training machine algorithms and enabling them to effectively identify relationships and patterns.

Another factor favoring the use of machine learning algorithms in this field is the presence of uniformity in the production of textile fibers. Production processes are subject to certain technological criteria, called maps, which must be respected regardless of the wide range of items and variations of customer orders.

3.2. Production data

Sourcing production data and preparing it for use in machine learning is often the most time-consuming stage of the overall forecasting process. The selection, proper preparation and processing of the data are the basis of success in building the model. Collecting production data in the textile industry can be challenging for a number of reasons – collecting data for different processes that use different types of raw materials and require different methods of processing and quality control. In some textile factories, the level of automation is low or outdated machines are used that do not support modern data collection methods. Therefore, some data must be collected and analyzed manually.

Global textile equipment manufacturers Uster and Loepfe use similar classifications and parameters in yarn production [13]. The parameters measured by the Uster instruments are:

1. ***CV%*** – coefficient of variation (Coefficient of Variation). Used to measure the unevenness or variability of a yarn or fiber. A lower value of CV% indicates a higher quality consistency, i.e. the yarn is more uniform in terms of thickness, length, strength, etc.
2. ***Thin*** - measures the sections of the yarn that are thinner than the set norm or the average thickness of the yarn. It is usually measured in meters per kilometer.
3. ***Thick*** - specification for the sections of the yarn that are thinner than the specified norm or the average thickness of the yarn. Similar to the Thin parameter, it is measured in meters per kilometer.
4. **Neps** - measures the number of "neps" for a given length of yarn, usually one kilometer. Neps are small, usually round formations in the yarn that can form during manufacturing processes such as spinning.
5. ***YF*** - this parameter is used to evaluate the overall yarn quality and is a combination of various individual metrics that have been measured and analyzed. YF stands for "Yarn Faults" and measures different types of yarn faults, e.g. thin places, thick places, curls, neps, etc. imperfections. It is measured in "numbers per 100 km".

Each of these parameters is important for the quality of the manufactured products. E.g. "Thin" and "Thick" places in the yarn can lead to problems in subsequent stages of textile production, such as weaving, knitting or dyeing. The presence of nepsis can cause problems in dyeing, weaving or knitting. In addition, neps can become visible in the final textile product, creating an uneven surface or defects, and can compromise the quality of the final textile product.

The other established system, Loepfe, uses a set of sensors and algorithms to detect foreign substances in the yarn and provides data and analysis to help manufacturers identify the source of the problem and take appropriate corrective action. The quality criteria investigated by Loepfe instruments used in this study are:

1. Class ***A1*** defects are "thick spots" in the yarn. These are areas where the yarn has a larger diameter than adjacent areas. They can occur for a variety of reasons, including irregularities in the spinning process, variations in fiber length and diameter, or problems with the thread take-up system.
2. ***A2*** means "thin places" in the yarn. Like Class A1, Class A2 defects can also affect the appearance, strength and performance of the final product.
3. ***B1*** errors count the number of "neps" in the yarn. They can be caused by a number of factors, including contamination, poor fiber quality and processing problems. These "knots" can affect the appearance and performance of the final product.
4. Class ***C1*** defects: C defects are defined as "slubs" in the yarn. Te are thicker areas in

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the yarn where the fiber has gathered, resulting in a visible lump or unevenness. These "breaks" can be caused by a variety of factors, including draw problems, variations in fiber length or diameter, and other factors. Like neps, slubs can affect the appearance and performance of the final product.

5. Parameter ***F*** refers to "foreign body", which can be any foreign material that is not part of the yarn or fiber being processed. Foreign bodies can be debris, metal particles, oil or other contaminants that can affect the quality of the final product.
6. ***I1*** refers to "Irregularity". Accounts for variations in yarn thickness or texture along its length. These imperfections can occur due to poor quality raw materials, uneven loading of machines, errors in settings or wear of components. These can lead to problems in the final product, such as weak spots in fabrics, processing problems or defects in finished products.

3.3. Characteristics of production data

In the incoming raw data of the textile fiber manufacturing process, there are two main problems/issues that need to be solved: the wide range in which the data varies and the measurement reporting period.

With continuous reading, the values of the monitored parameters can vary over a wide range. In general, such variations do not show a tendency towards deterioration or stabilization of the quality indicator, but may be the result of the influence of random factors. A single exceedance of a given critical limit for a given parameter shall not cause the production process to be stopped to adjust the machine.

A commonly used technique for reporting parameters is to average the values of the measurements. At the same time, only one value is taken for a selected time interval, which is the arithmetic mean value of all measurements performed. Key features related to data modeling for each of the quality parameters are:

- basic optimal value – this is a value that determines excellent fiber quality according to a set criterion;
- lower and upper limit according to specification – define the limits in which the quality standard is considered to be met;
- upper and lower control limits - set deviations from the base value, within the limits of which it is considered that the produced fibers are of good quality. Reading values outside these limits signals the need for machine adjustment;
- time interval – period for which measurements of quality parameters are reported;
- current value of a parameter – calculated as an arithmetic mean value for the parameter in a certain time interval.

Typically, control limits are set in the range between the specification limits and are 10% deviations from the baseline optimum value, and specification limits deviations are 15% from the baseline.

It is possible that the control limits have different values, with different quality requirements from different customers. Figure 2 shows an example quality tracking graph based on the total number of yarn faults. The tolerances for the upper and lower limits are 10% of the base value.

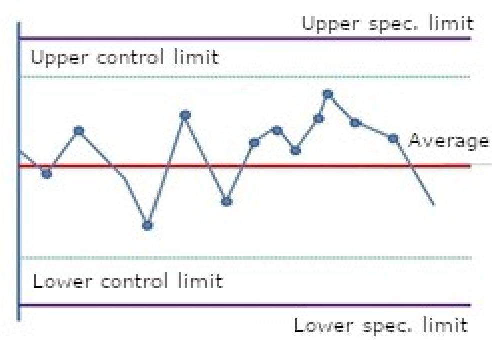

Figure 2. Example model for tracking the deviations of a given quality control parameter

The choice of measurement interval is essential. The departure of the current value of a parameter outside its control limits is a clear signal for the need for intervention, correction and additional examination of the raw material. Depending on the size of the lots and the deadline for production, the most suitable reporting period can be chosen. Too short a reporting period could cause control limits to be crossed frequently, and too long a time interval increases the possibility of late identification of quality problems. Different data reporting intervals result in a different amount of data for training machine algorithms and could therefore affect forecasting capabilities.

3.4. Machine learning algorithms

Machine learning is a subset of artificial intelligence that allows computer algorithms to learn directly from data and solve tasks in a way that is not pre-programmed. Choosing the most efficient algorithm for solving a given task is often difficult, due to the huge number of machine learning algorithms, the need to conduct experiments with each of them, and compare them in order to choose the best algorithm.

Suitable machine learning algorithms for building a model predicting the quality trend of the manufactured item are Linear Regression, Logistic Regression, Decision Tree and Random Forest.

Linear Regression is a simple form of machine learning in which a model is trained to predict numerical values by analyzing the relationship between multiple independent and one dependent variable [14]. Although this method has statistical roots, it is a core component of many machine models and algorithms for prediction and regression. It is characterized by simplicity, interpretability and efficiency, but is not effective in solving complex nonlinear problems.

Logistic Regression is a statistical method and model in machine learning used primarily for classification tasks [15]. Instead of predicting numerical values as in linear regression, logistic regression is used to predict probabilities of belonging to two or more classes.

A **Decision Tree** is a graphical model and algorithm in machine learning used to solve classification and regression tasks [16]. This model is called a "decision tree" because it represents decisions as a tree-like structure with a root, nodes, and leaves. Decisions are made along the path from the root of the tree to the leaves, with each leaf representing a final class or value. The advantages of this method are high interpretability and the ability to deal with complex data, but there is a risk of overtraining the model.

Random Forest is a powerful ensemble method in machine learning that is used for classification and regression tasks [17]. This method combines multiple decision trees and provides more robust and accurate predictions than single decision trees. In the random forest, the principle of "wisdom of the masses" (ensemble learning) is used, where more models are combined in order to achieve a better final result.

In the context of textile production, each of these methods can be used to predict, e.g. on the basis of historical data on the numerical values when a certain defect has occurred, to predict whether the manufactured item has a tendency for high scrap rates, without waiting for the completion of the production process.

4. EXPERIMENTS CONDUCTED AND RESULTS

The purpose of the experiment is to create a model that, based on various yarn quality parameters recorded in the production process for 20 days, will make a forecast for possible deviations in yarn quality for the 21st day.

4.1. Methodology

A standard methodology was used to conduct the experiment. Data were collected using Uster and Loepfe devices widely used in the textile industry. The parameters discussed above in the production of yarn - CV%, Thin, Thick, Neps and YF of Uster, and A1, A2, B1, C1, F and I1 - of Loepfe were investigated.

All experiments were conducted on single-item data. 4 methods were experimented - Linear Regression, Logistic Regression, Decision Tree and Random Forest. Data from the production process for 20 days was collected and a forecast was made for the 21st day. 80% of the data is used to train the algorithms and 20% is used to test and evaluate the models. Figures 3 and 4 show the studied parameters and their exemplary deviation from the base values within the production process.

The two experiments were carried out on the same technological process under the same repeated conditions, and differ only in the dataset used. In the first experiment, data taken at 5 min is used, and in the second - at 2 min.

Depending on the machines settings, defect data can be received every second, minute, hour or day. The conducted experiments are for predicting the values of each criterion separately. The data from the two Uster and Loepfe instruments cannot be combined and a prediction made on all the data at the same time. The use of a general criterion is not applicable because the criteria are strictly specific for different manufacturers. The principle of measurement of each device is strictly specific, as different manufacturers have a different way of measuring different characteristics. For these reasons, combining the data would not guarantee a better result.

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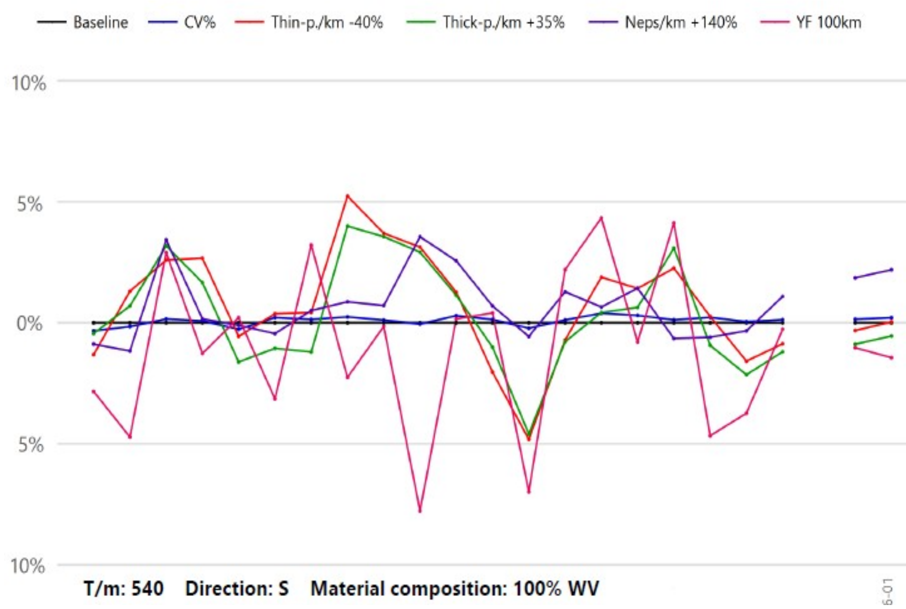

Figure 3. 21-day graph tracking quality using the criteria set by Uster

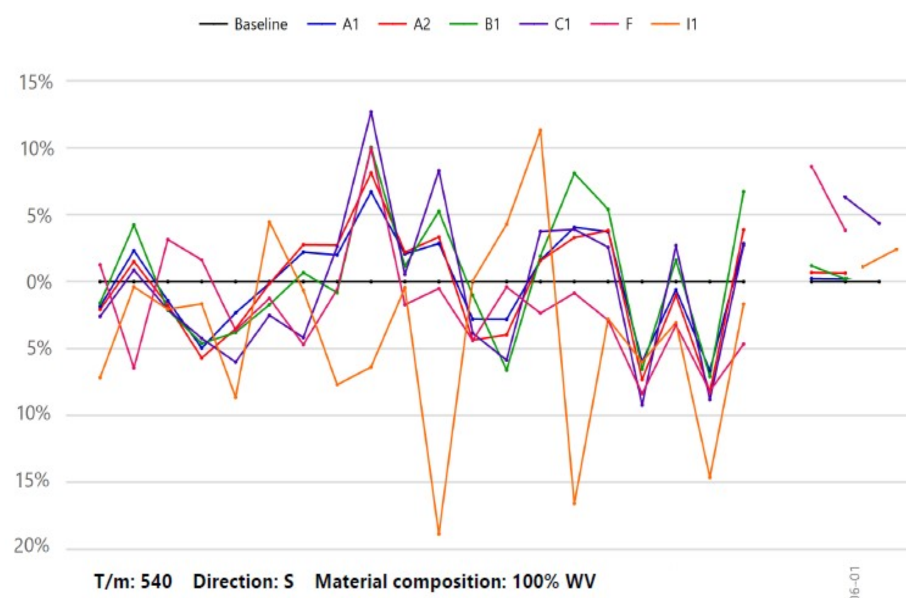

Figure 4. 21-day graph tracking quality using criteria set by Loepfe

4.2. Results

Addressing our first objective, which focuses on evaluating the accuracy of machine learning algorithms in textile fiber defect detection, the following results were obtained:

1. The first experiment was conducted with two datasets containing data recorded with Uster and Loepfe instruments. Each dataset consists of 5,760 records containing 5 types of characteristics and reported within 20 days, for 5 minute intervals. Models were created with the four algorithms - Linear Regression, Logistic Regression, Decision Tree and Random Forest. Initial results were not encouraging (table 1). The best results are achieved with the Decision Tree algorithm. The data coming from the Uster

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device turned out to have less deviation and this led to better prognostic results.

2. A second experiment was conducted to obtain better results. It again used two datasets, with data recorded with Uster and Loepfe instruments, but each dataset consisted of 14,400 records containing 5 types of characteristics and recorded over 20 days, at 2-minute intervals.

Significantly better results were achieved in this experiment. They are systematized in table 2. Here again the greatest accuracy is achieved with the Decision Tree algorithm.

These findings demonstrate a significant improvement in accuracy over traditional methods, thereby fulfilling our objective of showcasing the efficacy of machine learning in quality control.

Table 1. Day 21 prediction success rate with 5760 records

Algorithm	Criteria									
	Data from the Uster device				Data from the Loepfe device					
	CV %	Thin-p./km -40%	Thick-p./km +35%	Neps.km /+140%	YF 100km	A1	A2	B1	C1	I1
Linear Regression	54%	47%	53%	55%	48%	44%	59%	60%	56%	43%
Logistic Regression	59%	49%	57%	60%	51%	45%	61%	62%	58%	41%
Decision Tree	61%	51%	60%	64%	58%	50%	65%	68%	60%	47%
Random Forest	53%	44%	55%	57%	47%	42%	57%	58%	54%	40%

Table 2. Day 21 prediction success rate with 14400 records

Algorithm	Criteria									
	Data from the Uster device				Data from the Uster device					
	CV %	Thin-p./km -40%	Thick-p./km +35%	Neps.km /+140%	YF 100km	A1	A2	B1	C1	I1
Linear Regression	82%	76%	81%	55%	48%	81%	83%	85%	85%	83%
Logistic Regression	85%	81%	84%	60%	51%	82%	86%	89%	90%	82%
Decision Tree	91%	90%	93%	64%	58%	89%	91%	92%	93%	87%
Random Forest	80%	79%	86%	57%	47%	79%	81%	88%	87%	81%

In relation to our second objective of addressing specific challenges in applying machine learning to textile quality control, our analysis revealed the following:

- **Comparison with traditional quality control methods**. Traditional quality control methods have long been the cornerstone of textile manufacturing. These methods, including visual inspection, manual sorting, and statistical process control, have served as essential tools for ensuring product quality in this industry. While they offer valuable insights, they also come with inherent limitations.
- **Challenges in traditional methods**. Visual inspection, for instance, relies on human operators and is subject to subjectivity and fatigue, potentially leading to oversight of subtle defects. Manual sorting processes are labor-intensive and can introduce variability in the sorting criteria. Statistical process control, although valuable, may not always capture nuanced variations.
- **Integration of machine learning**. Machine learning, with its capacity for automation and data-driven decision-making, offers a promising solution to address these challenges. By leveraging machine learning algorithms, textile manufacturers can achieve consistent and automated defect detection, reducing their reliance on manual inspection methods.
- **Complementary approach**. It's essential to recognize that machine learning should not necessarily replace traditional methods but rather complement them. By combining the strengths of both approaches, manufacturers can benefit from enhanced quality control processes that are both efficient and reliable.
- **Challenges faced in implementing machine learning**. However, implementing machine learning in textile quality control is not without its own set of challenges. Gathering high-quality training data, developing and fine-tuning machine learning models, and seamlessly integrating these technologies into existing production processes require careful consideration and expertise.

In conclusion of this chapter, our study sheds light on the potential of machine learning to address specific challenges in textile quality control. By offering a more automated and consistent approach compared to traditional methods, machine learning represents a valuable addition to the arsenal of quality control tools available to textile manufacturers.

Our study differentiates itself in the field of business model innovation and big data analytics by employing a unique multidimensional analysis framework, which contrasts with the more traditional single-dimensional approaches used in existing studies. For instance, the research conducted by Smith and Jones [18] in their exploration of big data's role in marketing strategies focused primarily on consumer behavior analytics. In contrast, our study broadens this scope by integrating operational, financial, and consumer data, providing a more comprehensive view of business model impacts.

Additionally, unlike the study by Khang, Alex & Abdullayev [19], which examined big data analytics in the context of large multinational corporations, our research centers on small to medium-sized enterprises (SMEs), a segment often overlooked in this field. This focus on SMEs offers novel insights, particularly in how these entities can leverage big data analytics for competitive advantage and innovation in a different scale and context compared to larger corporations.

Furthermore, our methodology incorporates real-time data analysis, a feature not commonly explored in existing literature. This real-time approach allows for a more dynamic understanding of the interplay between business model adjustments and market responses, filling a significant gap in the current research landscape.

5. CONCLUSION

Effective management of the production process in textile production is extremely important for achieving high quality of manufactured products and for optimizing the work process. The measurement and monitoring of key parameters for the quality of the manufactured product and the prediction of a possible sharp deviation from the norm of any of the criteria, enables a timely reaction on the part of the management and technical staff and taking preventive measures to minimize accidents and unplanned shutdowns.

The article presents the results of conducted experiments aimed at predicting possible deviations for the 21st day, based on a database of yarn production for 20 days. Machine learning algorithms were used - Linear Regression, Logistic Regression, Decision Tree and Random Forest. Best predictive results are achieved with Decision Tree.

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Predicting potential problems in the production process in yarn production has many advantages. Detecting yarn quality problems before they become serious enables the manufacturer to take action in advance, thus preventing defects and rejects of manufactured goods. With a warning of impending problems, the production process can be managed in a more flexible and sustainable way, risks of equipment failure can be identified in advance, maintenance and repair teams can prepare and react more quickly to fix problems.

Machine learning algorithms can also be used to optimize other aspects in the manufacturing process, e.g. trend analyzes comparing the performance of different machines or raw materials; optimization of planning schedules, in order to maximize efficiency in batch planning, the operation of spinning and winding machines, etc.; identifying worst performing components, e.g. spindles, etc.

In conclusion, our study's scientific contribution lies in its demonstration of the tangible benefits of machine learning in textile quality control, setting a new benchmark for the industry. We believe that our findings will not only inform future research endeavors but will also catalyze the adoption of machine learning solutions in textile manufacturing.

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