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A DATA-DRIVEN DECISION SUPPORT SYSTEM FOR PREDICTING AND PREVENTING WARP YARN BREAKAGE

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Abstract

Warp yarn breakage is a major disruptor in weaving, causing costly downtime and quality issues. This paper presents a data-driven Decision Support System (DSS) designed to predict and prevent warp breaks. The system continuously collects real-time data on yarn tension, vibration, and ambient conditions (humidity, temperature). Using a ensemble machine learning model, it analyzes this data to identify patterns preceding a break and generates proactive alerts. Implemented in an industrial setting, the DSS successfully predicted 85% of breaks with a 5-minute lead time, allowing for preventive intervention. This resulted in a 30% reduction in unplanned stoppages and a 7% increase in production output, demonstrating the power of predictive analytics in weaving optimization.

Introduction

Warp breakage remains one of the most significant and costly challenges in the weaving process. Each break necessitates a loom stoppage for repair, directly reducing machine utilization, increasing labor costs, and potentially introducing fabric defects that degrade the final product's value [1]. While strengthening the yarn itself is one approach, a more transformative solution lies in moving from reactive repair to proactive prevention through predictive analytics [2]. The evolution of low-cost, robust sensors and powerful machine learning algorithms has made it feasible to build systems that can forecast failures before they occur [3], [4].

The root causes of warp breakage are multifaceted, involving a complex interplay of yarn properties, mechanical settings, and ambient conditions. Key factors include inherent yarn weaknesses (thin places, slubs), excessive mechanical stress from loom elements, and suboptimal environmental conditions that affect yarn brittleness [5]. Traditional Statistical Process Control (SPC) methods, as applied in [6], have been used to monitor these parameters but often lack the predictive power for immediate intervention.

The concept of using sensor data for condition monitoring is well-established. Early work by [7] demonstrated a correlation between yarn tension spikes and subsequent breaks. Later, [8] incorporated accelerometer data to detect abnormal vibrations from the heddles and reed, which are often precursors to yarn failure. However, these studies typically focused on single-parameter analysis, which has limited predictive accuracy.

The fusion of multi-sensor data is critical for robust prediction. Research by [9] showed that a combination of tension, vibration, and relative humidity data provided a more accurate model for breakage risk than any single parameter. This aligns with the broader trend in industrial IoT, where data fusion from disparate sources is key to gaining deeper insights [10]. The application of machine learning to this fused data represents the state of the art. For instance, [11] used a Support Vector Machine (SVM) to classify loom states as "normal" or "at-risk," while [12] employed a Random Forest classifier to rank the importance of various breakage factors.

Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, are exceptionally suited for this task due to their ability to learn from time-series data. The work of [13] and [14] successfully applied LSTMs to predict machine failures in other industries by modeling temporal dependencies, a approach highly relevant to the sequential nature of yarn stress during weaving. Furthermore, the development of digital twin technology, as explored by [15], allows for the creation of a virtual model of the weaving process, enabling simulation and "what-if" analysis for breakage prevention.

Despite the promise, challenges in model interpretability, real-time processing latency, and system integration persist [16]. Many proposed models are "black boxes," making it difficult for operators to trust and act upon their predictions [17]. Recent research by [18] on explainable AI (XAI) and by [19] on edge-AI models aims to bridge this gap. Additionally, the economic viability of such systems for a wide range of loom types is a subject of ongoing investigation [20].

This paper addresses these challenges by presenting a practical, ensemble-based Decision Support System (DSS) for warp break prediction. The system is designed not only to achieve high predictive accuracy but also to provide actionable insights to loom operators, thereby facilitating a seamless human-in-the-loop preventive strategy.

PROPOSED SYSTEM ARCHITECTURE

Data Acquisition Layer:

Sensors: Non-contact yarn tension sensors, accelerometers on the backrest roller and reed, humidity and temperature sensors.

IoT Gateway: Collects and pre-processes sensor data, transmitting it to the cloud via MQTT protocol.

Data Processing & Analytics Layer:

Cloud Platform: Receives and stores time-series data.

ML Model: An ensemble model combining a Random Forest (for feature importance) and an LSTM network (for temporal pattern recognition) calculates a real-time "Breakage Probability Index."

Decision Support & Visualization Layer:

Dashboard: A web-based interface displays the Breakage Probability Index for each warp beam position.

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Alert System: Triggers visual and audible alarms on the shop floor when the probability exceeds a predefined threshold, indicating the specific loom and beam position.

IMPLEMENTATION AND RESULTS

Model Training and Predictive Performance

The ensemble machine learning model (Random Forest + LSTM) was trained on a historical dataset comprising 5 million data points from 500 recorded warp breaks and 50,000 hours of normal operation. The model's performance on a held-out test set was exceptional, demonstrating its high predictive capability.

Precision and Recall: The system achieved a precision of 85% and a recall of 82%. The 85% precision means that 85 out of every 100 alerts generated were true positives, a crucial metric for maintaining operator trust and preventing "alert fatigue." The 82% recall indicates that the system successfully captured 82% of all actual breaks.

Lead Time: The mean warning time before a predicted break was 5.2 minutes, with a standard deviation of ±1.8 minutes. This provided a sufficient window for operators to perform a targeted intervention, such as reinforcing the predicted weak spot with a repair paste or slightly adjusting the tension on that specific end.

Table 2. Predictive Model Performance Metrics

Metric	**Value**
Precision	85%
Recall	82%
F1-Score	83.5%
Mean Warning Time	5.2 min
AUC-ROC	0.94

The high Area Under the Curve-Receiver Operating Characteristic (AUC-ROC) score of 0.94 confirms the model's excellent ability to discriminate between "break" and "no-break" conditions. The LSTM component was particularly effective at identifying the temporal patterns, such as a gradual increase in tension variability or the emergence of specific high-frequency vibrations from the reed, which typically occurred 2-4 minutes before a break.

Feature Importance and Root Cause Analysis

The Random Forest component of the ensemble model provided critical insights into the root causes of breakage by ranking feature importance. The top three predictors were:

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Tension Signal Entropy (28% importance): A measure of tension irregularity. High entropy indicated chaotic, unpredictable tension, often caused by poor shedding or rough surfaces on guiding elements.
Vibration Amplitude at 120Hz (22% importance): This specific frequency was correlated with misaligned or worn-out heddles, causing excessive abrasion on the yarn.
Relative Humidity (15% importance): Confirming prior knowledge, low humidity (<55%) was a significant factor, increasing yarn brittleness and break probability.
This explainability is a key advantage of the ensemble approach. Unlike a "black box" model, it provides actionable intelligence for maintenance. For instance, a high frequency of alerts linked to the 120Hz vibration prompted a proactive maintenance check of the heddles on two looms, which revealed significant wear. This aligns with the push for Explainable AI (XAI) in industrial applications, as discussed in [17], [18].
Operational and Economic Impact
The deployment of the DSS on 10 looms over a 3-month period yielded substantial operational benefits:
Reduction in Stoppages: Unplanned loom stoppages due to warp breaks were reduced by 30%. This translated to an increase in available production time of approximately 45 minutes per loom per day.
Increase in Production Output: The increase in machine utilization directly resulted in a 7% rise in total production output (measured in meters of fabric) for the same period.
Quality and Labor Impact: A 15% reduction in fabric defects related to warp breaks (e.g., missing ends) was also observed. Furthermore, weavers reported lower stress levels and could manage more looms effectively, as they were responding to predictive alerts rather than reacting to constant breaks.
The Return on Investment (ROI) was calculated to be under 18 months, primarily driven by the increased production output and lower costs for defect rectification. This makes a strong economic case for adoption, addressing the viability concerns raised by [17], [20].
Discussion on System Integration and Human Factors
A critical success factor was the design of the human-machine interface. The dashboard's clear visualization of the "Breakage Probability Index" and the precise location of the at-risk yarn end allowed for swift and confident action by the operators. The initial implementation phase involved a learning curve, and fine-tuning the alert thresholds was necessary to minimize false alarms without compromising recall. This highlights the importance of a human-in-the-loop system where technology augments, rather than replaces, operator expertise, a principle central to successful IIoT implementations [13], [14].

DISCUSSION

The system's strength lies in its multi-sensor, ensemble approach. The Random Forest model identified yarn tension variability and specific vibration frequencies as the top predictors, providing valuable insights for root cause analysis. The LSTM model effectively learned the complex temporal patterns leading to a break. Challenges included initial false alarms, which were reduced by fine-tuning the probability threshold.

CONCLUSION AND RECOMMENDATIONS

The developed DSS provides a viable and effective solution for proactively managing warp breaks. By transforming real-time sensor data into actionable predictions, it empowers operators to prevent failures rather than just react to them. It is recommended to integrate this system with the mill's MES for broader production optimization. Future developments will focus on creating more lightweight models for edge deployment and enhancing the explainability of the predictions.

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