Integration of Artificial Intelligence and Machine Learning for Intelligent Monitoring in Full Shoe Production Lines

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Integration of Artificial Intelligence and Machine Learning for

Intelligent Monitoring in Full Shoe Production Lines

1Akshayaraman M, 2Sadhanandham J, 3Loganathan T, 4Poovarasan H,

5Jones I, 6David Manosh S, 7Nithiyanantha Vasagam S*

1Senior Scientist, 2, 3Scientist, 4Project Assistant, CSIR- Central Leather Research Institute, Chennai

5Project Internship, Easwari Engineering College, Ramapuram, Chennai

Ref. No. TF-86/P

6,7Senior Principal Scientist, CSIR- Central Leather Research Institute, Chennai

Abstract

The footwear manufacturing sector, particularly full shoe production lines, continues to rely heavily on Manual Monitoring Processes (MMP) for production tracking, quality control, and decision-making. Such dependence on human-centric monitoring leads to inefficiencies, limited transparency, delayed corrective actions, and challenges in achieving sustainable manufacturing objectives. This research investigates the integration of Artificial Intelligence (AI) and Machine Learning (ML) frameworks to transform conventional footwear production lines into intelligent, data-driven manufacturing systems. The study aims to comprehensively map the shoe production process, quantify the limitations of MMP using secondary macroeconomic indicators from the World Bank (2001– 2023) and primary data collected from leather footwear manufacturing units, and develop AI/MLenabled monitoring architectures for real-time production transparency. Methodologically, the work employs systematic literature review, workstation-level data acquisition, vector autoregressive modelling, and interrupted time series analysis to evaluate production dynamics. AI/ML-based simulation and visualization tools are designed, validated at laboratory scale, and proposed for phased factory-level deployment. Preliminary results reveal significant deficiencies in scalability, responsiveness, and predictive capability

Correspondence author email : nvasagam.clri@csir.res.in

within MMP-driven systems, while AI/ML integration demonstrates strong potential for enhanced productivity, sustainability, and intelligent decision support. The study positions intelligent manufacturing as a critical enabler for the future competitiveness of footwear start-ups, MSMEs, and large-scale production units.

Keywords: Manual Monitoring Processes (MMP), shoe production line, AI/ML models, data visualization, intelligent manufacturing, footwear manufacturing, production transparency, sustainable production, vector autoregressive modeling, time series analysis

1. Introduction

The global footwear industry operates in a highly competitive environment, characterized by fluctuating demand, complex supply chains, and increasing pressure for sustainable and transparent manufacturing practices [1]. Despite advancements in mechanization and automation, most full shoe production lines covering cutting, closing, lasting, assembly, and finishing still depend on Manual Monitoring Processes (MMP) for production control and performance evaluation [2]. These processes rely on human supervision for data collection, interpretation, issue detection, and corrective action, often resulting in delayed responses and limited system scalability.

In recent years, Artificial Intelligence (AI) and Machine Learning (ML) have emerged as transformative technologies across manufacturing sectors, enabling predictive analytics, real-time monitoring, and autonomous decision-making [3]. While intelligent manufacturing frameworks have been successfully deployed in process industries such as chemicals and pharmaceuticals [4], their adoption in footwear manufacturing remains limited and fragmented. This gap underscores the need for a structured, data-driven approach tailored to the unique operational characteristics of shoe production lines.

This study addresses this gap by proposing an AI/MLintegrated monitoring framework aimed at replacing conventional MMP with intelligent, real-time production transparency systems.

2. Research Objectives

The primary objectives of this research are:

1. To map the complete footwear production line and identify monitoring-intensive workstations.

2. To quantify the limitations of Manual Monitoring Processes using secondary macroeconomic data and primary industrial inputs.

3. To develop AI/ML-based analytical, visualization, and simulation models for intelligent production monitoring.

4. To propose a scalable framework for real-time deployment of AI/ML systems in footwear manufacturing units.

3. Methodology

3.1 Literature Review and Data Acquisition

A comprehensive literature review was conducted covering intelligent manufacturing, AI/ML applications in production systems, and digital monitoring frameworks [3– 6]. Secondary macroeconomic data including GDP

contribution, CPI trends, FDI inflows, and global trade statistics from 2001 to 2023 were sourced from World Bank datasets to contextualize industrial productivity trends [7]. Primary data were collected through structured questionnaires administered to leather footwear manufacturing units, focusing on production delays, defect rates, labor dependency, and monitoring challenges.

3.2 Secondary and Primary Data Collection

Data collection is carried out using both secondary and primary sources to ensure robustness and reliability.

 Secondary data includes publicly available datasets such as World Bank indicators, industry reports, government publications, and historical production records.

 Primary data is collected through structured questionnaires, interviews, and direct observations from industrial units.

This mixed-data approach enables triangulation, improves data validity, and provides both macro-level trends and micro-level operational insights relevant to the research objectives. The mapped production stages and monitoring characteristics are summarized in Table 2.

3.2 Production Line Mapping

Footwear production line mapping involves the systematic documentation and analysis of the end-to-end manufacturing process, including material flow, machine utilization, labor involvement, cycle times, and production bottlenecks. Visualization tools such as process flow diagrams and value stream mapping are employed to represent the complete production system clearly. This approach enables a thorough understanding of operational inefficiencies and the identification of non-value-adding activities. The mapped production line establishes a baseline for performance evaluation and serves as a critical input for subsequent gap analysis, optimization, and system modelling stages.

3.3 MMP Gap Analysis

Manufacturing Maturity Practice (MMP) Gap Analysis is conducted to evaluate the difference between the current state of manufacturing practices and the desired or benchmarked maturity levels. This analysis assesses dimensions such as technology usage, process integration, workforce skills, data-driven decision making, and automation. By quantifying these gaps, critical improvement areas are identified. The results provide strategic insights for enhancing operational efficiency and guide the selection of appropriate analytical and AI-based interventions.

3.4 Statistical and Time Series Modelling

Statistical modelling is employed to analyse relationships among key variables and to study temporal effects within the data.

1. Vector Auto Regression (VAR) is used to examine dynamic interdependencies between multiple time-series variables such as production output, efficiency, and resource utilization.

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Where is the vector of production indicators

(output rate, delay, defect rate), Constant vector representing baseline production conditions independent of time-lagged effects,

represents coefficient matrices, Vector

of lagged production variables at time and is the error term [8].

2. Interrupted Time Series (ITS) analysis is applied

to assess the impact of specific interventions, policy changes, or technological implementations over time.

Where , Continuous time variable representing the chronological progression of production observations, Binary intervention indicator variable:

Baseline level of the production metric prior to AI/

MLintervention, Pre- intervention trend (slope) of the

productionmetric, Immediate level change in the production metric following AI/ML deployment, Change in trend (slope) of the production metric attributable to AI/ML intervention and Random error term accounting for unexplained variability, assumed to be independently and identically distributed.

Production

Key Operations

Monitoring

AI/ML Intervention

Stage

Mode (MMP)

Potential

Material cutting, nesting

Vision-base defect detection

Manual inspection

Cutting

ML-based quality prediction

Closing Stitching, seam joinin

Supervisor checks

Predictive cycle-time analytics

Lasting Shape forming

Manual timing

Real-time process optimization

Assembly Sole attachment

Operatordependent

Automated quality grading

Finishing Polishing, inspection

Visual inspection

Table 1. Shoe Production Line Mapping and

Monitoring Characteristics

3.5 AI/ML Framework Development

In this stage, Artificial Intelligence and Machine Learning techniques are applied to develop predictive, classification, or optimization models based on the processed dataset. Algorithms such as regression models, decision trees, random forests, or neural networks may be employed depending on the research objective. Feature selection, model training, tuning, and evaluation are systematically performed to ensure accuracy and generalizability. The AI/ML models aim to enhance decision-making, predict performance outcomes, and simulate alternative production scenarios.

3.6 Validation and Deployment

The final stage focuses on validating the developed statistical and AI/ML models using appropriate performance metrics such as accuracy, RMSE, precision, recall, or robustness checks. Validation ensures model reliability and practical applicability. Upon successful validation, the models are deployed within a decisionsupport framework or pilot implementation environment. This stage bridges the gap between theoretical research and real-world application, demonstrating the practical value and scalability of the proposed methodology.

4. AI/ML-Enabled Production Monitoring Architecture

As shown in the Fig. 1, AI/ML-Enabled Production Monitoring Architecture for the Footwear Industry integrates real-time data from machines, sensors, vision systems, and ERP/MES platforms to create a unified, intelligent manufacturing environment. Shop-floor data such as cycle time, machine health, defect images, energy usage, and operator inputs are processed through edge devices and cloud-based analytics layers, where AI/ML models predict bottlenecks, quality deviations, and equipment failures. Computer vision enables automated inspection of cutting, stitching, lasting, and finishing operations, while predictive models support dynamic line balancing and preventive maintenance. The architecture

provides actionable dashboards and alerts for supervisors and management, enabling data-driven decisions, improved productivity, reduced rework and downtime, and consistent product quality across diverse footwear manufacturing processes.

4.1 Physical Layer

The Physical Layer represents the foundational level of the architecture where real-world data originates. It comprises sensors, machines, and workstations deployed across the operational environment. Sensors continuously capture raw parameters such as temperature, pressure, vibration, speed, and energy consumption, while machines and workstations generate operational and production-related data. This layer acts as the primary interface between the physical system and the digital infrastructure, enabling real-time monitoring of industrial processes.

4.2 Data Acquisition Layer

The Data Acquisition Layer is responsible for collecting, aggregating, and transmitting data from the physical layer to higher-level systems. It utilizes IoT gateways and PLC/SCADA interfaces to ensure reliable communication between heterogeneous devices and control systems. This layer handles protocol translation, data buffering, and secure transmission, thereby enabling seamless integration of legacy industrial equipment with modern digital platforms.

4.3 Data Processing Layer

The Data Processing Layer focuses on transforming raw data into meaningful and structured information. Key functions include data cleaning, which removes noise, inconsistencies, and missing values, and feature extraction, which identifies relevant variables and patterns necessary for analytical modelling. This preprocessing stage is essential to improve data quality and enhance the accuracy and efficiency of subsequent analytical and machine learning models.

4.4 AI / ML Analytics Layer

The AI/ML Analytics Layer constitutes the intelligence core of the architecture. It applies advanced analytical techniques such as prediction models, anomaly detection, and optimization algorithms to processed data. Predictive models support forecasting of system performance and failures, anomaly detection identifies abnormal operational behavior, and optimization algorithms assist in improving efficiency, resource utilization, and production planning. This layer enables proactive and data-driven decision-making.

Fig 1. AI/ML Enabled Production Monitoring System

5. Comparison of MMP vs AI/ML-Based Monitoring

5.1 Manual Monitoring Process (MMP)

The Fig 2. Shows the generic comparison of Manual Monitoring Process (MMP) and AI/ML based Monitoring process, the MMP refers to traditional supervisory methods where system performance, operational conditions, or quality parameters are observed and assessed by human operators. Monitoring is largely dependent on human experience and judgment, making it prone to subjectivity, fatigue, and inconsistencies. This approach is typically

4.5 Visualization & Decision Layer

The Visualization and Decision Layer provides an interactive interface for end users, including managers, engineers, and decision-makers. It presents insights through dashboards, alerts, and decision support systems, facilitating real-time situational awareness and strategic planning. By converting analytical outputs into actionable knowledge, this layer supports timely interventions, continuous improvement, and informed operational decisions.

suitable for low-complexity systems but becomes inefficient as system scale and data volume increase.

5.1.1 Manual Data Entry

Manual data entry involves human operators recording observations, measurements, or inspection results into logs or information systems. This process is timeconsuming and susceptible to transcription errors, missing values, and delays. The reliance on manual input also limits data frequency and accuracy, restricting the potential for timely analysis and informed decision-making.

5.1.2 Periodic Inspection

Periodic inspection refers to scheduled checks performed at fixed time intervals rather than continuous monitoring. While this method helps identify visible faults or deviations, it often fails to detect transient anomalies or early-stage failures that occur between inspections. As a result, emerging issues may remain unnoticed until they escalate into critical problems.

5.1.3 Delayed Decision-Making

In manual monitoring systems, decision-making is often delayed due to the time required for data collection, validation, reporting, and human interpretation. This latency reduces the system’s responsiveness to abnormal conditions and limits the organization’s ability to take proactive corrective actions in real time.

5.1.4 Reactive Control

Reactive control represents a response strategy where corrective actions are initiated only after a fault or failure has already occurred. This approach typically results in higher downtime, increased maintenance costs, and reduced operational efficiency, as interventions are performed after performance degradation rather than before it.

5.2 AI/ML-Based Monitoring

AI/ML-based monitoring leverages artificial intelligence and machine learning algorithms to continuously observe system behavior and performance. These models learn patterns from historical and real-time data, enabling automated interpretation of complex system dynamics. This approach significantly enhances monitoring accuracy, scalability, and adaptability compared to manual methods.

5.2.1 Automated Data Capture

Automated data capture utilizes sensors, IoT devices, and integrated information systems to collect data continuously without human intervention. This ensures high-resolution, real-time data acquisition with minimal errors. Automated

capture forms the foundation for advanced analytics and supports large-scale, data-driven decision frameworks.

5.2.2 Real-Time Analytics

Real-time analytics involves the immediate processing and analysis of incoming data streams to detect deviations, trends, or anomalies as they occur. By eliminating analysis delays, real-time analytics enables organizations to maintain situational awareness and respond promptly to dynamic operational conditions.

5.2.3 Predictive Alerts

Predictive alerts are generated using machine learning models that forecast potential failures or performance degradation before they occur. These alerts are based on learned patterns, correlations, and anomaly detection techniques, allowing preventive actions to be taken in advance and reducing unplanned downtime.

5.2.4 Autonomous Decision Support

Autonomous decision support systems recommend or automatically execute optimal actions based on analytical insights and predefined objectives. By integrating predictive intelligence with control mechanisms, these systems reduce human dependency, enhance consistency, and support proactive, data-driven operational strategies.

5.3 Metrics

5.3.1 Response Time

Response time refers to the duration between the occurrence of an abnormal event and the initiation of corrective action. In manual systems, response time is typically high due to human intervention and processing delays. Advanced AI-based monitoring significantly reduces response time by enabling automated detection and rapid decision-making.

5.3.2 Defect Rate

Defect rate indicates the frequency of errors, faults, or non-conforming outputs. Manual monitoring often leads

to higher defect rates due to delayed detection and inconsistent inspections. AI/ML-driven systems reduce defect rates by enabling early fault prediction and continuous quality monitoring.

5.3.3 Productivity

Productivity measures the efficiency with which resources are utilized to achieve desired outputs. Automated monitoring and decision support improve

Fig 2. Comparison of MMP vs AI/ML-Based Monitoring

productivity by minimizing downtime, optimizing processes, and reducing manual workload.

5.3.4 Transparency

Transparency refers to the visibility and traceability of system operations and decision processes. AI/ML-based monitoring enhances transparency through real-time dashboards, explainable analytics, and comprehensive data logging, supporting better governance and informed stakeholder decision-making.

6. Results and Discussion

The analysis reveals that MMP-driven production systems suffer from poor scalability, delayed responsiveness, and limited transparency. Statistical modelling such as VARt and ITSt indicates strong interdependencies between production delays and manual data handling inefficiencies [8]. AI/ML-based simulations demonstrate improved production predictability, faster anomaly detection, and enhanced decision-making capabilities.

Drawing parallels with chemical plant monitoring systems, the proposed framework enables autonomous feedback loops, reducing human intervention while improving sustainability metrics such as energy efficiency and waste minimization [4,9]. These findings highlight the novelty and industrial relevance of AI/ML integration in footwear manufacturing.

7. Essential Requirements for an Effective Production Sector

For effective transformation of the footwear production sector, the study identifies key requirements: real-time data acquisition, interoperable digital infrastructure, skilled human-AI collaboration, and continuous learning systems. AI/ML-enabled monitoring is positioned as a foundational element for achieving resilient, transparent, and sustainable manufacturing ecosystems.

8. Conclusion

This research demonstrates that integration of AI and ML into full shoe production lines offers a viable pathway to overcome the inherent limitations of Manual Monitoring Processes. By enabling real-time transparency, predictive analytics, and intelligent decision support, the proposed framework significantly enhances production efficiency and sustainability. In addition, the adoption of AI/MLdriven monitoring and control systems contributes to a

substantial reduction in production cycle time and qualityrelated defects, while improving process consistency, firstpass yield, transparency and overall operational throughput. The work contributes to the emerging discourse on intelligent footwear manufacturing and provides actionable insights for start-ups, MSMEs, and large-scale production units. Future work will focus on full-scale industrial deployment and longitudinal performance evaluation.

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