Digital transformation technologies for conveyor belts predictive maintenance: a review

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ABSTRACT

The availability of condition-monitoring data has increased due to internet of things (IoT) technologies, providing information on various parameters like vibration, temperature, current, and voltage. Cloud computing and big data facilitate the prevention of failures and estimation of remaining useful life through advanced mathematical models and artificial intelligence (AI) techniques. These enable prompt and suitable maintenance actions. This article conducts a systematic review of digital transformation technologies, including cloud computing, edge computing, AI, machine learning (ML), and TinyML, in predictive maintenance for conveyor belt systems. This article reviews how these digital transformation technologies improve predictive maintenance strategies for conveyor belts. The systematic review summarizes the results and challenges of various methodologies used in conveyor belt systems and suggests areas for further research. This paper aimed to serve as a useful resource for researchers, practitioners, and industry professionals seeking insights into current predictive maintenance technologies for conveyor belt systems. The takeaways of the review are expected to ignite discussion on efficient and proactive maintenance strategies and promote the development of innovative solutions for ensuring the reliability and longevity of conveyor belt systems in the digital era.

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1. INTRODUCTION

Conveyor belts are indispensable for efficient transportation of materials across a range of industries, including mining, logistics, and civil engineering. They play a crucial role in coal mines and are vital for the transportation of bulk materials in shipping ports. Their applications include extraction, smelting, power generation, and other related fields [1]–[3]. As the conveyor belts play critical role in transportation, it is essential to regularly inspect the running status of belt conveyors and maintain their smooth operation [4].

Manufacturing requires a digital transformation strategy that sets objectives and compares them with the existing state. The integrated business process management (IBPM) framework combines human-centric and technological methods to provide a customizable roadmap for manufacturers to embrace digital transformation. The present day frameworks focus on the impact of Industry 4.0 on small and medium-sized manufacturing enterprises (SMEs). The novelty of these frameworks emphasize sustainability and modernization and hence successfully adopted by manufacturing SME, resulting in improved performance and sustainable practices [5]–[7]. The predictive maintenance method is shifting the gears in the industry applications of belt conveyors as it involves real-time health assessments of machinery using integrated sensors. Predictive maintenance method employs digital transformation technologies, such as internet of

things (IoT), Industry 4.0, machine learning (ML), cloud computing, and edge computing to bring optimum and efficient maintenance. The method comprises of four important phases: data acquisition from diverse sensors, data preprocessing for accuracy, fault diagnosis, and decision making for tailored maintenance strategies. The digital transformation technologies like IoT, deep learning algorithms, big data analytics, artificial intelligence, automation, and robotics play important role to execute the phases of predictive maintenance. The scope of this article include the following.
- Detailed analysis on the possibility of making conveyor belts as smart entities.
- Digital transformation in the manufacturing and mining industries with a focus on industry growth.
- Review of the recent research on predictive maintenance methods that employed integrated sensors to monitor machinery health in real time using IoT, Industry 4.0, ML, and cloud computing.
- Review of application of digital transformation technologies and their impact in predictive maintenance of conveyor belt.

2. DIGITAL TRANSFORMATION TECHNOLOGIES FOR PREDICTIVE MAINTENANCE

Digital transformation technologies are essential for Industrial Metaverse, enabling immersive experiences and shaping future possibilities. Digital transformation streamlines business operations through social media, big data, mobile applications, and cloud computing. The challenges include data security and system interoperability. Digital transformation technologies comprise a comprehensive array of cutting-edge tools and tactics that enable businesses to achieve success in the digital age. These resources include the IoT, artificial intelligence (AI), ML, cloud computing, big data analytics, edge computing, cybersecurity, blockchain, augmented reality (AR)/virtual reality (VR), and automation/robotics. These technologies empower organizations to streamline their operations, improve customer service, and sustain a competitive edge in a digital environment. In the Industry 4.0 era, conveyor belt systems underwent a digital revolution fueled by technologies such as IoT, cyber-physical systems (CPS), and the internet of services [8]. Schwertner *et al.* [9] examined the application of digital transformation technologies in conveyor belt systems, focusing on crucial technologies such as the IoT, ML, deep learning, cloud computing, and edge computing. Digital transformation technologies for predictive maintenance are shown in Figure 1.

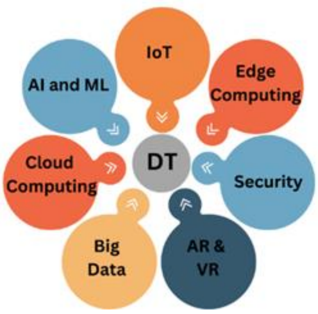

Figure 1. Digital transformation technologies

Fedorko [10] explored the integration of digital transformation technologies and conveyor belt systems to emphasize bidirectional data communication via CPS, and thereby enabling intelligent protocols. Beyond health monitoring, this system coordinates tasks within the conveyor and transportation system and transforms the conveyor into a smart entity. Leveraging the advantage of IoT, it continuously collects and shares real-time data, making the conveyor adaptive and responsive. This digital integration on the conveyor and transportation sparked interest in the industry discussions on digital transformation. Ulas [11] addressed how digital technologies are reshaping manufacturing for small and medium enterprises SMEs, stressing the necessity for adapting structures and practices to stay competitive. It also underscores the importance of assessing the costs and benefits of digital tools for thriving in today's business landscape. Gopal *et al.* [12] highlighted how digital transformation, leveraging IoT, analytics, ML, and AI, addresses healthcare challenges and enhances patient outcomes and cost management. It also emphasizes benefits, such as optimized care, cost reduction, evidence-based decisions, and operational efficiency for both patients and providers. Predictive analytics maximizes performance by utilizing sensors and the IoT for efficient production. Deep learning enhances manufacturing performance supported by AI and IoT for predictive analytics [13]. An investigation was conducted by Barnewold and Lottermoser [14] to determine key digital transformation technologies in the mining sector. The results indicate that essential technologies include automation, robotics, the IoT, big data, real-time data analysis, ML, AI, and three-dimensional printing. Another study [15] explored artificial intelligence in drilling and production, addressing challenges such as stuck pipes and hydrate formation. This underscores how digital transformation enhances oil well operations, fostering collaboration between industries and research centers.

3. APPLICATIONS

Table 1 summarizes the digital transformation technologies employed for the predictive maintenance of conveyor belt systems. The IoT is the most commonly utilized technology, whereas ML is used to a lesser extent, and cloud and edge computing are rarely employed by researchers in this field.

Table 1. The summary of studies applying digital transformation technologies in conveyor belt maintenance

Ref	Application	IoT	ML	Cloud
[16]	Real-time maintenance management	April USB Beacon 306, TCRT5000 infrared sensor, arduino nano 33 BLE, and Raspberry Pi	Data analysis	Thing speak
[17]	Predictive maintenance of mining machines	Temperature, vibration, current, and pressure measurement		Cloud for storage and analysis
[18]	Detection of potato harvester drive belt abrasion	Anisotropic magneto-resistive sensors	Auto correlation	
[19]	Predictive maintenance on belt conveyors using digital twin	Sensor data	Remaining Useful Life, AI based object detection	
[20]	Predictive maintenance framework for conveyor motors	Vibration, speed, tension, current, temperature, acceleration sensors	CNN, GAF, PCA, SVM, parameterized rectifier linear unit	
[21]	Underground mine conveyor maintenance	Temperature sensor, Robot, Humidity, CO, H2S, NOx, or velocity and thermal imaging	image processing	
[22]	Predictive maintenance of conveyor using anamoly detection	Current sensors, load sensors	One class SVM, KNN and kernel PCA	
[23]	AI-based predictive maintenance	Gyroscope, accelerometer, and geomagnetic sensor		
[24]	Identifying the conveyor belt faults	accelerometer, arduino, data logging	Fast fourier transform	
[25]	Predictive conveyor belt wear models		Manually created dataset, linear regression, random forest	
[26]	Predictive maintenance to decrease conveyor belt downtime	LiDAR sensors and temperature measurement		
[27]	Predictive maintenance of belt conveyor systems		Analysis	

3.1. IoT

The combination of research emphasizes how technology, including the IoT, revolutionizes conveyor systems. Hegde *et al.* [28] demonstrated IoT-enhancing waste sorting using RFID, inductive sensors, and cloud connectivity, improving recycling efficiency. Ananthi *et al.* [29] presented an intelligent conveyor system using RFID and the IoT for inventory control, tracking enhancement, and product management. An advanced conveyor system sorts waste with sensors and Arduino revolutionizes waste segregation [30]. These studies showcase the transformative power of the IoT in improving efficiency, accuracy, and automation in industrial processes. A Raspberry Pi 3 B+and stepper motor were utilized to create a conveyor belt speed control model in Python programming. Kamalakannan and Devadharshin [31] designed a model to demonstrate the effect of weight variation on the conveyor belt by gradually adjusting the speed level. Gupta *et al.* [32] investigated the application of IoT technology for the predictive maintenance of conveyor belts in airport baggage systems. It focuses on transitioning from conventional periodic maintenance approaches to real-time IoT-based methods. It employed ML to identify anomalies and diagnose defects, with a preference for the random forest model in evaluating actual data. As per Lodewijks *et al.* [33], IoT and big data improve conveyor monitoring, offering 24/7 surveillance and predictive maintenance to reduce the downtime. Bibancos *et al.*,introduced combination of IIoT and LoRaWAN in mining sector to monitor conveyor belt rollers. This method enables early failure detection, prevents damage, and reduces unplanned shutdowns and production losses, demonstrating the advantages of Industry 4.0 in enhancing mining operations [34]. Raffik *et al.* [35] introduced an inventory tracking system using industrial automation tools and IIoT for improved efficiency, minimal downtime, and optimized production rates based on demand and supply insights.

Some of the researchers focused on fault diagnosis in conveyor belt systems to highlight innovative methodologies and advancements in predictive maintenance and intelligent fault diagnosis. They offer distinct insights of fault detection in coal production conveyor applications. By employing IoT and light gradient boosting machine (LGBM) models, Wang *et al.* [36] successfully identified faults and issues warnings, as demonstrated in a three-month field test. It introduces a remote monitoring system, offers accurate fault diagnosis, and showcases real-time capabilities, surpassing conventional methods in data processing, autonomous analysis, and security. Martínez-Parrales and Téllez-Anguiano [37] proposed a fault detection system for vibrating conveyors that leverages the IoT and vibration analysis for continuous monitoring, and achieves a high detection accuracy of 98.01%. Mingjin Wang *et al.* [38] introduced an IoT-based fault diagnosis system for roller fault detection in belt conveyors. It uses sensors to capture audio data and applies advanced techniques, such as convolutional neural networks and spectral clustering, to achieve an accuracy of 96.7%. Hasnita and Herri [39], developed a wireless vibration detector using ATmega microcontrollers and a MPU6050 sensor. It detected up to 13% of 12 g vibrations and found that closer sensor proximity increased the detection. The above studies highlight various methods and advancements in the diagnosis of faults in conveyor belt systems, including predictive maintenance, vibration-based monitoring, and intelligent audio analysis. They are crucial for maintaining the operational efficiency and safety of conveyor belt systems. The integrated approach in the above-mentioned studies showcase the pivotal role of IoT technology in the comprehensive monitoring and maintenance of conveyor belts. It enables real-time data collection, facilitates machine-learning algorithms, ensures continuous operational oversight, optimizes production outcomes, and enhances industrial processes [40], [41]. Hamid and Alneamy [42] compared IoT protocols for the development of IoT products and found that MQTT is stable in IoT, CoAP connects queues, and XMPP suits multithreading. Therefore, IoT plays a pivotal role in enhancing fault diagnosis, predictive maintenance, and health monitoring in conveyor belt systems using diverse data sources, such as image, vibration, audio, and sensor data.

3.2. AI and ML

Gerike *et al.* [43] highlighted common diagnostic criteria for mining machine reducers, focusing on short-term predictions by monitoring variations related to load and speed. Additionally, the study enhances the evaluations of gear units and predictive models for belt conveyor systems. Another study by Kiangala and [20] introduced a practical predictive maintenance framework for conveyor motors in small manufacturing units, aligned with Industry 4.0 with the help of ML and convolutional neural network (CNN) with time-series imaging, and achieved accurate fault classification. The adaptability of the model handles various data types, employing principal component analysis (PCA) for dimensionality reduction and gramian angular field (GAF) for image conversion. By achieving approximately 100% accuracy, the CNN model reduces the risk of missed critical faults or unnecessary maintenance. Liu *et al.* [27] introduced a new method for belt conveyor idlers, blending operational data and real-time monitoring to improve reliability. It adjusts monitoring thresholds based on live conditions and outperforms traditional methods. This dynamic approach promises improved conveyor maintenance strategies. Kiangala *et al.* [44] conducted a study in a small bottling plant to demonstrate the potential of Industry 4.0 principles in small and medium- SMEs. It focuses on the early detection of faults in conveyor motor systems and implements a predictive maintenance strategy. The proposed predictive maintenance strategy achieved by collecting and analyzing real-time vibration data to create maintenance schedules for motors. It showcased the benefits of Industry 4.0 and provided an effective approach to predictive maintenance for SMEs. The authors of the following study, Al-Kahwati *et al.* [19] suggested a solution for the predictive maintenance of belt conveyor systems, which is crucial for achieving production objectives. This solution integrates a digital twin, degradation model, and vision-based hazard detection. The validation results showed the efficacy of the solution in predicting the component status and detecting hazards.

AI and ML research involves algorithms imitating human intelligence for tasks, recognizing patterns, and making decisions based on data without explicit programming. Many studies have used deep learning for image classification in conveyor-belt systems. Guo *et al.* [4] introduced an improved mobile cloud computing (MCC)-cycle GAN model, which demonstrated fast detection, high performance, and sample generation for enhanced neural network training. It effectively identifies damaged conveyor belt surface images despite requiring extensive training time. Furthermore, this article highlights the application of ResNet-34, ResNet-50, VGG 16, Inception v3, and AlexNet algorithms in image classification. Santos *et al.* [45], presented a method for identifying soil on conveyor belts using DenseNet161 for optimal accuracy and a balance between precision and recall. ResNet18 is recommended for resource-constrained situations, in which performance is desired. Dingran Qu *et al.* [46] utilized an adaptive deep convolutional network (ADCN) to diagnose and monitor conveyor belt impairments in real time. This model demonstrates superior performance in classifying and localizing issues during operation, outperforming the SVM-based methods. A holistically nested edge detection (HED) model employing deep convolution networks exhibits precise conveyor belt deviation detection, with edge detection errors below 16 mm and resilient anti-jamming features, ensuring swift and accurate resolution of conveyor belt issues [47]. Another article proposed a method where it integrates IoT sensor information with ML algorithms to enhance fault detection in coal production conveyor belts. The system aims to accurately identify deviations, slippage, and tearing faults, thereby enabling remote monitoring and real-time fault diagnosis. The fault identification and proactive maintenance system are based on anomaly detection using a rule-based bottom-up approach [36], [48]. The MCC-CycleGAN, ResNet-34, ResNet-50, VGG 16, Inception v3, AlexNet, DenseNet161, ResNet18, ADCN, HED model, and LGBM algorithms have been employed in various studies to address different aspects of conveyor belt systems, including image classification, fault detection, real-time monitoring, and proactive maintenance.

3.3. Cloud computing, edge computing and tiny ML

Cloud computing enhances conveyor-belt systems by offering improved data storage, analysis, and management. IoT sensors and ML algorithms enable real-time monitoring and predictive maintenance, ensuring scalable and reliable operation. In addition, cloud computing provides cost-effective and flexible resources over the internet. Salhaoui *et al.* [49] introduces a drone-based monitoring model for conveyor belts in concrete plants and processing images in the cloud for real-time analysis. Intercommunication challenges are addressed through node-RED computation and fog on the IoT gateway. Wang *et al.* [50] presented a cloud-based framework that facilitates robot communication and negotiation in smart factories by connecting cloud, robot, and client terminal layers. Through dynamic reconfiguration, it enables seamless communication across layers and negotiation for companion robots, showcased in a candy packing application, thereby enhancing factory operations. Edge computing boosts real-time processing for IoT with a SiPEED board deploying deep neural networks on conveyor belt images using MobileNet 0.75 for rip detection in iron processing plants, enhancing efficiency despite resource constraints [51]. Liu *et al.* [52] introduced a hardware system leveraging edge devices for improved bottle cap detection, utilizing FPGA-based processing for faster algorithm execution, correcting back caps, optimizing detection, and resource efficiency.

TinyML empowers the IoT by enabling local data analysis and decision-making. Research articles on TinyML demonstrated its effectiveness in power tool monitoring during construction, achieving 90.6% accuracy while conserving power. Additionally, TinyML excels in structural health monitoring (SHM), achieving high accuracy in impact localization and real-time analysis on low-power devices, with future strategies for dataset expansion and signal processing refinement [53]. Edge computing and devices, such as SiPEED boards and FPGA-based modules, help improve predictive maintenance by overcoming network constraints, enhancing security, and increasing speed. This enables swift local analysis using TinyML for tool and structural health monitoring. These advancements promise smarter solutions to industry challenges, including conveyor systems and structural health monitoring applications [54]–[56].

4. RESULTS AND DISCUSSION

This study extensively reviewed fault diagnostics, prediction, feature extraction, fault classification, and decision-making, significantly enhancing our understanding of predictive maintenance and fortifying the reliability of industrial machinery. Likewise, the integration of digital transformation technologies such as IoT, Industry 4.0, machine learning, cloud computing, and edge computing optimizes traditional industrial systems, paving the way for more efficient maintenance strategies. Predictive maintenance relies on integrated sensors employing IoT, Industry 4.0, machine learning, cloud computing, and edge computing for the real-time monitoring of machinery health. This review underscores the pivotal role of digital transformation technologies that are specific to predictive maintenance in belt conveyer systems. Out of all digital transformation technologies, IoT technology has emerged as a pivotal facilitator, enhancing fault diagnosis, predictive maintenance, and health monitoring in conveyor belt systems by leveraging diverse data sources, such as images, vibrations, audio, and sensor data. Besides that, multiple studies have successfully applied diverse machine learning algorithms such as MCC-CycleGAN, ResNet-34, ResNet-50, VGG 16, Inception v3, AlexNet, DenseNet161, ResNet18, ADCN, HED model, and LGBM to address different aspects of conveyor belt systems. These algorithms have been used as proactive maintenance strategies. In future research, the integration of edge computing shows promising results to significantly enhance predictive maintenance capabilities, enabling on-site fault detection. TinyML is also looks promising as it can be used for rapid local analysis and promising intelligent solutions for handling industrial challenges.

The presented review confirms the potential of digital transformation technologies to improve the efficiency of both conveyor systems and structural health-monitoring applications.

5. CONCLUSION

This review explored how sensors and digital transformation technologies improve the predictive maintenance of conveyor belt systems. It encourages researchers to incorporate innovative models based on digital information technologies in the maintenance methods and strategies of belt conveyer systems. It emphasizes the transforming power of IoT, AI, and cloud computing in the industrial applications. They ensure machinery health assessments to improve the efficiency of industrial utilities. The authors of this review expected this article to spark interest in the combination of digital transformation technologies and belt conveyer system maintenance methods to bring more sophisticated and intellegent models for more reliable conveyor systems and pave the way for future advancements in conveyor belt maintenance methodologies.

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