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Artificial Intelligence-Based Device For Pipe Manufacturing

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ABSTRACT
The steel sector is undeniably a cornerstone of the global economy, making vital contributions to construction, automobile manufacturing, and pipe production. This paper confidently explores the transformative effects of deep learning, particularly through the applications of machine vision and artificial intelligence, on enhancing performance benchmarks within the steel industry. Given the sector's crucial role in producing construction materials, automotive components, and high-quality energy and fluid transmission pipes, the pursuit of ongoing technological advancements is not just necessary; it is essential. Machine vision and artificial intelligence are powerful drivers in achieving precise data analysis and significantly improving industrial efficiency. This research decisively examines the increasing significance of these technologies, demonstrating their substantial impact on refining industrial operations within the steel industry. Acknowledged as indispensable tools for progress, machine vision and artificial intelligence are significantly shaping the sector's technological landscape. This study conducts a thorough examination to explore the diverse applications of machine vision and artificial intelligence in the steel industry. By analyzing recent trends and innovations, the paper aims to deliver a comprehensive overview of how these technologies are actively revolutionizing the industrial landscape. The findings clearly highlight the critical role of deep learning in enhancing productivity, driving innovation, and elevating global standards within the steel sector.

KEYWORDS – Artificial Intelligence, Machine learning, Upstream, Oil and Gas Industry, Steel Pipe Industry.

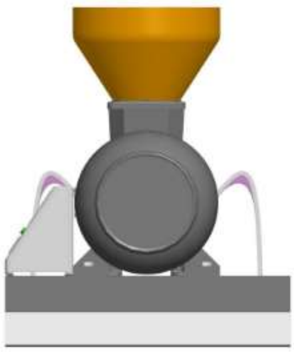
INTRODUCTION-[1] The steel industry stands out as a vital cornerstone of modern civilization, recognized for its accessibility, cost-effectiveness, and widespread application. This sector plays an indispensable role in our daily lives and in various industrial processes. As a key pillar of the national economy, it provides essential materials for contemporary construction, transportation, bridges, vehicles, ships, household appliances, electric power, marine engineering, and countless other aspects of everyday life. Nevertheless, the steel industry currently confronts significant challenges, including high levels of carbon dioxide emissions, subpar working conditions, environmental pollution, and safety concerns related to extreme temperatures and toxic gases. Additionally, workers face high labor intensity and repetitive tasks. In response to these pressing issues, large-scale steel companies have proactively adopted automation, embraced information technology transformations, and made substantial upgrades over recent decades. These strategic initiatives have dramatically improved production efficiency and elevated automation levels within the industry, paving the way for a more sustainable and responsible future. As industrialization and urbanization in globally, the steel industry is facing oversaturation. Despite its competitiveness, the sector struggles with a shortage of high-end products, long research and development cycles, low worker efficiency, inconsistent quality, and low profitability. To address these challenges, the industry needs to transform its manufacturing model to offer more flexible, customized products while reducing production cycles. Key concerns include enhancing product quality, improving automation, shortening development timelines for new materials, and supporting sustainable economic growth. These issues can be tackled using emerging technologies like the Internet, artificial intelligence, and big data analytics.. Intelligent manufacturing is a powerful approach that seamlessly integrates modern information technologies such as 5G, digitalization, networking, and artificial intelligence into traditional manufacturing processes. This strategy is transforming the industry, significantly enhancing productivity, intelligence, and flexibility. It has become a focal point in global research and industrial applications, marking a decisive shift away from outdated production and sales models toward a dynamic, customer-driven customization strategy. Leading nations, including Germany, the United States, and Japan, are making intelligent manufacturing a cornerstone of their national development plans. Their goals are ambitious: to elevate the intelligence of the manufacturing sector, establish state-of-the-art intelligent factories that prioritize personalized customization and optimal resource allocation, and foster deeper integration of customers and business partners within the value creation process. This proactive approach is set to revolutionize productivity in the manufacturing industry. Based on the foundational concept of intelligent manufacturing, numerous experts have conducted comprehensive research demonstrating its significance. Since the proposal of Industry 4.0, various critical infrastructure issues necessary for its development have been identified, facilitating advancements in manufacturing that efficiently promote short product life cycles and extreme mass customization. Key areas of focus include construction methodologies, self-organization within the Industry 4.0 context, standardization, integrated information systems, training and education, and the application of artificial intelligence. In the transformative landscape of Industry 4.0, intelligent manufacturing applications are being powerfully explored across a wide range of industrial sectors, including heavy industry, supply chain management, production management transformation, and small- and medium-sized enterprises (SMEs). Leading researchers such as Ghobakhloo, Kamble, Osterrieder, Ching, Leng, and Chauhan effectively showcase the impactful 4.0 technologies essential for building sustainable industrial systems. The digital twin stands out as a revolutionary technology in intelligent manufacturing, providing real-time insights into manufacturing systems and enabling the proactive prediction of potential failures. This technology is pivotal in driving intelligent cyber-physical integration and digital transformation in the manufacturing industry. Moeller et al. have rightly identified the digital twin as a major catalyst for the digital transformation of intelligent manufacturing. Tan’s evaluation of financial management models within intelligent manufacturing demonstrates how organizations can optimize costs and enhance financial performance. Furthermore, Wu's innovative application framework for a digital-twin-driven intelligent manufacturing system for ships highlights the vast potential of this technology. Li et al. have successfully established a digital twin framework that assesses the green performance of intelligent manufacturing, employing an effective hybrid model based on fuzzy rough sets AHP, multistage weight synthesis, and PROMETHEE II. Zhang's collaborative framework shows how digital twin technology can seamlessly blend complex product design, production, and service processes. Li's research powerfully argues that traditional manufacturing companies must embrace digital transformation, as illustrated by the compelling case study of Haier Group’s “Internet Plant. ”Wang et al. have carried out an in-depth analysis of the framework, development, key technologies, and applications of big data analytics (BDA) in intelligent manufacturing systems. The impressive growth in data generated by manufacturing systems is largely attributed to advancements in the Internet of Things (IoT), 5G, and cloud computing technologies. Deng’s research on spatial agglomeration and optimal layout in intelligent manufacturing supply chains delivers actionable insights crucial for informed business and government decision-making. Ge et al. have thoroughly assessed the intertwined concepts of supply chains, industry chains, cyber-physical systems, big data, IoT, cloud computing, industrial transformation, and value chains within intelligent manufacturing. Li has laid a robust theoretical foundation for harnessing big data-driven technology in decision-making, emphasizing its significant benefits and critical motivating factors. Guo et al. have developed an intelligent decision support system (DSS) that leverages data-mining technology to create an IoT-based DSS for the manufacturing industry, empowering decision-makers to make informed and strategic choices. Moreover, Yan et al. have elevated the concept of an intelligent workshop through digital twinning by presenting a well-defined theoretical model and system framework, along with detailing three essential technologies for virtual simulation control. The ongoing research in this field confidently outlines the future of intelligent manufacturing, demonstrating its immense transformative potential across various industries.[1][2] The steel industry is marked by mass production facilitated by large-scale equipment. Given the intricacies of operating various types of machinery and the substantial volume of materials involved, the Japanese steel sector has actively embraced innovative technologies to enhance production structures and improve operational efficiency. During the 1970s, the integration of process computers became established; these computers were required to operate in real-time within manufacturing plants continuously. They automatically computed operational parameters for production facilities and gathered data for quality control based on production schedules determined by higher-level computing systems.The principles of factory automation (FA) and computer-integrated manufacturing (CIM) were already integrated into routine practices, leading to a substantial increase in both the quantity and complexity of software developed for process computers that supported manufacturing operations. Recognizing that software managing manufacturing processes is critical to ensuring product quality—an essential component of competitive advantage—the company developed the Nippon Steel computer-aided software engineering system (NSCASE) in the 1980s. This initiative established a framework for efficient internal software development.In the latter half of the 1980s, leveraging accumulated expertise in computer utilization, the company designed a novel type of industrial computer defined by its expandability, ease of integration, compatibility, and open architecture. This system was extensively deployed across the company's facilities and was subsequently combined with NSCASE, marketed as a system product within the company's electronics, information, and communication division. By the 1990s, the company was capable of autonomously producing both hardware and software, thereby creating a diverse array of control application software applied to steel manufacturing processes across all facilities. The digitalization of electrical and instrumentation controllers was primarily driven by maintenance and management objectives, such as reducing costs and errors through the minimization of electrical components like relays and wiring, while also enhancing control precision to mitigate drifts and noise typical of analog amplifiers. With advancements in data processing efficiency and memory capacity, innovative control methods and programming languages were developed. Consequently, the functionalities of electrical (E) and instrumentation (I) controllers began to converge with those of process computers (C). The notion of integrated EIC systems emerged in the mid-1980s, culminating in the adoption of single-vendor systems by the decade's end, followed by multivendor systems in the early 1990s. The practical application of these combined systems revealed the necessity of delineating the functions of E, I, and C, aligning them with their specific programming languages and computational methodologies, rather than maintaining them as a singularly packaged control system. In the 2000s, while E, I, and C evolved along distinct trajectories, they maintained compatibility and effective communication through Ethernet and other generalized communication networks proliferating during the Internet era.[2]

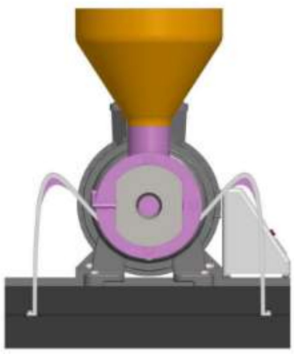
MATERIAL & METHODES : [3] Fouling, or concentration polarization, hinders a membrane's ability to perform at its maximum efficiency and can occur in any membrane-based process. The primary applications of AI in the field of membranes focus on fouling prevention. Various AI and machine learning techniques have been employed to predict different fouling parameters, such as permeate flux and transmembrane pressure (TMP), achieving improved accuracy compared to traditional mechanistic models. Artificial Neural Networks (ANNs) were the first intelligent models used to predict and more accurately control membrane fouling. Following this, fuzzy logic (FL) has also been utilized to model membrane fouling and develop automated systems for its management. Additionally, Model Trees (MTs) serve as hierarchical structures comprised of nodes and branches, which can be applied to various fouling prevention mechanisms. The internal nodes of these trees include tests on input variables, allowing MTs to identify certain subdomains characterized by regression functions. Unlike other models, MTs can partially explain the hidden relationships between different parameters in complex water treatment systems..Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) are commonly used methods for optimizing fouling, incorporating intelligent data pre-processing to minimize fouling and cleaning costs. Optimized key parameters such as transmembrane pressure (TMP), pH, feed temperature, and filtration time using GA to manage fouling in oily wastewater ultrafiltration. It also applied GA to define minimum and maximum flux values. They introduced a GA-based multi-objective optimization for efficient oil filtration from industrial wastewater. Yusuf et al. (2017) presented a model-based controller for the Submerged Membrane Bio-Reactor (SMBR), where PSO optimized the controller's cost function. Additionally, Drews et al. (2007) created an optimization framework that automatically identifies dominant filtration mechanisms.Numerous hybrid intelligent models effectively harness advanced modeling methods and optimization techniques. A notable example is the work by Chew et al. (2017) and Coppola et al. (2021), who developed a robust hybrid model integrating a physical model with a Multilayer Perceptron Artificial Neural Network (MLPANN) to accurately predict fouling parameters in ultrafiltration water treatment. Clustering, a powerful machine learning technique, plays a significant role in membrane filtration processes by thoroughly analyzing the effects of temperature on sludge properties, the structure of the cake layer, and fouling in anaerobic Submerged Membrane Bioreactors (SMBR) (Alwatban et al. 2019; Osman et al. 2019). This technique is also instrumental in categorizing data across various membrane fouling challenges. Moreover, the application of image recognition technology provides precise monitoring of membrane performance, enabling the optimization of filtration conditions (Huyskens et al. 2011).Numerous hybrid intelligent models effectively harness advanced modeling methods and optimization techniques. A notable example is the work by Chew et al. (2017) and Coppola et al. (2021), who developed a robust hybrid model integrating a physical model with a Multilayer Perceptron Artificial Neural Network (MLPANN) to accurately predict fouling parameters in ultrafiltration water treatment. Clustering, a powerful machine learning technique, plays a significant role in membrane filtration processes by thoroughly analyzing the effects of temperature on sludge properties, the structure of the cake layer, and fouling in anaerobic Submerged Membrane Bioreactors (SMBR) (Alwatban et al. 2019; Osman et al. 2019). This technique is also instrumental in categorizing data across various membrane fouling challenges. Moreover, the application of image recognition technology provides precise monitoring of membrane performance, enabling the optimization of filtration conditions (Huyskens et al. 2011). [3][4] This paper presents a comprehensive analysis of the technologies and tools designed to enhance artificial intelligence (AI) strategies within the context of Industry 4.0. It explores the critical necessity of AI in this domain and identifies the ongoing challenges that obstruct its development. As society braces for the ramifications of the fourth industrial revolution (4IR), which is fueled by technological advancements, AI, and Industry 4.0, the body of literature addressing the societal implications of this transformation is burgeoning. Nonetheless, this area remains inadequately explored, particularly concerning AI's potential role in poverty alleviation, infrastructure advancement, and the achievement of sustainable development goals (SDGs).In the 21st century, there has been a marked increase in investments in AI, driven by the availability of extensive datasets, advanced computing hardware, and innovative methodologies. This framework has enabled the application of machine learning to various academic and industrial challenges. AI has evolved from a specialized academic discipline to an integral component of contemporary social and economic technologies.

In light of the identified advantages associated with the implementation of AI in industrial settings, AI-driven methodologies that leverage complementary technologies serve to streamline production and supply chain management processes. The work of earlier researchers focused on data management across different phases of the product lifecycle. One application involves the deployment of AI for data management, while the integration of big data enhances efficiency, quality, safety, and sustainability within smart manufacturing and industrial practices. The authors provide a thorough and current overview of the latest advancements and future opportunities for AI and big data applications within Industry 4.0 technologies.

Moreover, an additional area that could enrich this discussion is a comprehensive review of data management throughout the entire production cycle, potentially encompassing other AI-related applications and technologies not currently addressed. Other research has concentrated on quality assurance within product manufacturing, highlighting monitoring and control throughout the production cycle. Such research offers a broader perspective compared to studies confined to specific domains. For example, Corti et al. (2021) investigate quality management across products, services, and multiple stages of the production cycle. This article examines AI and related technologies through the lens of customer satisfaction and the enhancement of product performance. However, it does not adequately address implementation details or system architecture nor does it focus on data and system management.Based on this analysis, the forthcoming article aims to provide a more holistic perspective that encompasses both design and quality control aspects at the production level, with the objective of enhancing these two categories while thoroughly investigating AI-related methods and technologies within the industrial sphere. Given that AI and related technologies are being perceived as solutions to various challenges in Industry 4.0, recent literature has increasingly addressed this subject matter.[4][5] Big data is conventionally defined as the vast quantities of rapidly generated, complex, and varied information that necessitate the utilization of advanced technologies for capturing, storing, distributing, managing, and analyzing data. This concept is characterized by six fundamental attributes, commonly referred to as the 6 V's: volume, velocity, variety, veracity, variability, and value. Volume pertains to the enormous amount of data, typically ranging from petabytes to zettabytes. Velocity refers to the speed at which data is produced and the timeliness required for its analysis and subsequent action, with a positive correlation between the velocity of data and its value and reliability. Variety denotes the structural diversity within datasets, as data can exist in various forms, including structured, semi-structured, and unstructured types. Veracity addresses the quality and trustworthiness of the data. Variability indicates that data can flow at different rates, making its management more complex. Value emphasizes the importance of deriving meaningful insights and knowledge from the data. Effective processes are essential for transforming vast amounts of swiftly changing and diverse data into actionable insights. This transformation frequently involves the application of big data management and analytical technologies, which are integral components of the broader framework for extracting insights from big data. In recent years, the application of big data technologies has expanded significantly across various sectors, including manufacturing, services, finance, and beyond. For instance, Li et al. proposed a model aimed at guiding future applications of big data in energy economy modeling. They highlighted pertinent challenges such as data collection costs, ownership, and privacy, advocating for modelers to critically assess fundamental dynamic assumptions, datasets, and the big data collection and analysis tools that underpin their models. This model could facilitate research into the effects of electric vehicle charging on power systems. Moreover, uncertainty estimation may be applied to comprehensively evaluate future energy systems characterized by decentralized electricity networks. Machine learning technologies possess the capability to manage high-dimensional data and to reveal hidden relationships within intricate and dynamic contexts. A successful machine learning model can ascertain the connections between input and output parameters using sufficient samples, a task often difficult to replicate through experimental or simulation methods. Prominent machine learning algorithms include linear regression, artificial neural networks (ANN), support vector machines, support vector regression, and decision trees. Many researchers favor employing machine learning algorithms such as ANN due to their exceptional efficiency. As a contemporary computational model, ANN has seen extensive and rapid application in addressing various complex real-world challenges. Its popularity arises from its strong information processing capabilities, learning potential, high parallelism, fault tolerance, nonlinearity, noise tolerance, and generalization abilities.[5]

OBSERVATIONS AND INTERPRETATION





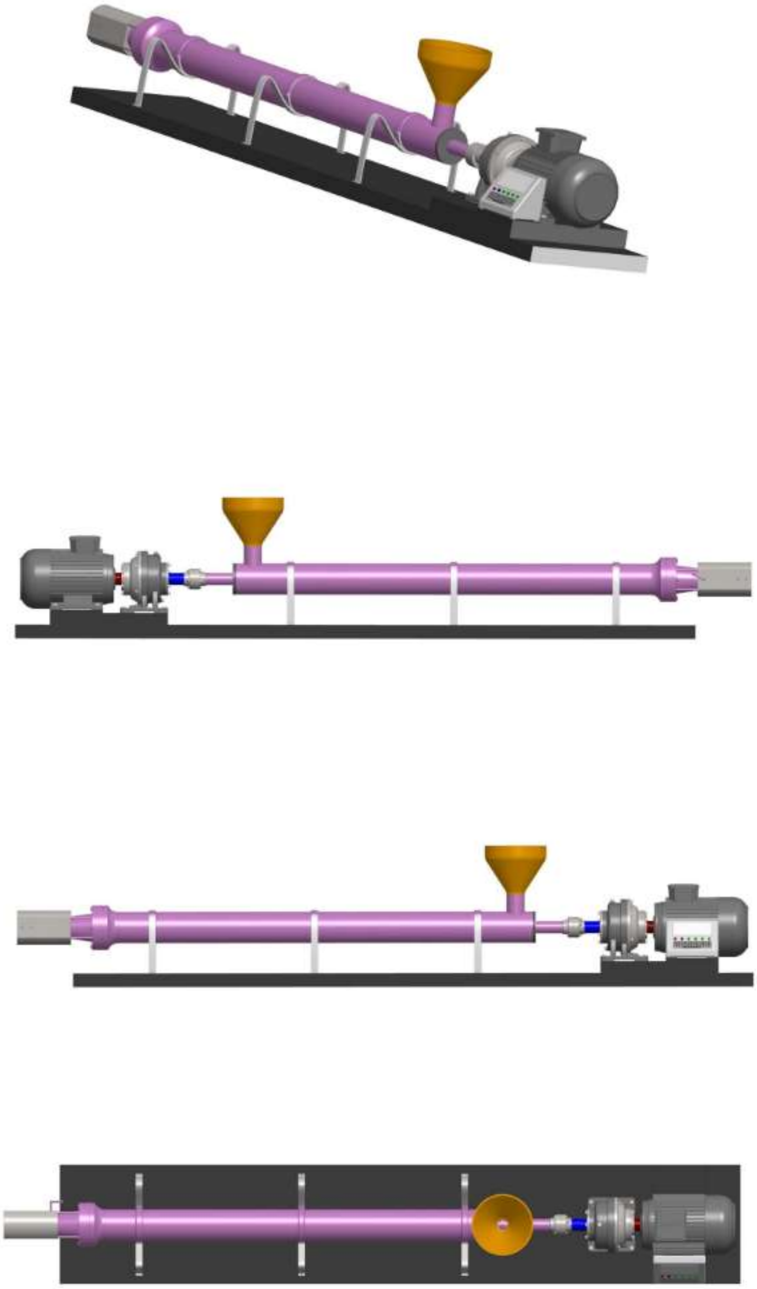


Figure-1 (All seven images are from UK Design number: 6373844

The same design is used for practical experiments for both Ultrasonic Testing (UT) and digital X-ray systems required a high degree of manual intervention, especially near the pipe ends. This end-zone testing is crucial because it's where defects are most likely to occur, and when pipes are joined in the field, the ends must be defect-free. Manual synchronization of the pipe's seam with the UT transducers or digital X-ray equipment was time-consuming and prone to human error, posing safety risks and creating inefficiencies in production.

However, the introduction of AI-based design has automated this process, significantly enhancing both productivity and safety. The design includes a Y-shaped funnel part, strategically placed near a motor, that collects data on the weld seam location. This information is transmitted to a Programmable Logic Controller (PLC), which then rotates the pipe to align the weld seam accurately. A middle portion, marked in purple, acts as a buffer zone to ensure proper seam alignment before the pipe reaches the AI-based flat portion for final testing.

This system continuously monitors the pipe and eliminates the need for manual adjustments by the operator. The AI-based sensors start collecting data as soon as the pipe begins moving, locking in the seam's position when detected. The final flat portion of the design helps synchronize the seam precisely, allowing NDT testing to begin without stopping the pipe. The entire process is fully automated, meaning operators no longer have to enter the conveyor area to adjust the pipe manually, significantly improving safety.

The impact of this design has been profound. It has eliminated the need for human involvement in pipe alignment for UT and digital X-ray testing, increased our production capacity by 30%, and significantly improved our ability to detect defects near the pipe ends. Previously, operators had to stop the pipe and manually synchronize it using a laser pointer, a process that took approximately 25 to 30 seconds. With the new system, this synchronization happens automatically, reducing cycle time by the same margin while maintaining, and even enhancing, quality and accuracy.
In conclusion, AI-based design has been instrumental in advancing the efficiency, safety, and quality of manufacturing processes.

RESULTS : [5]The primary objective of machine learning is to develop a robust model that excels across various dimensions. However, real-world conditions often present challenges that deviate from this ideal. Ensemble learning effectively addresses this issue by integrating multiple models to create a powerful and comprehensive supervised model. The principle behind ensemble learning is clear: when one weak classifier errs, others can rectify that mistake.We present a groundbreaking hybrid approach that combines Multilayer Perceptron (MLP), Support Vector Regression (SVR), and CatBoost to accurately predict energy consumption. The innovative structure of our proposed hybrid model is depicted in Figure 3. This model not only trains the CatBoost, MLP, and SVR algorithms but also effectively synthesizes their forecasting results to ensure superior accuracy.[5][6]The successful implementation of data-driven methods in the petroleum industry requires a strong understanding of both petroleum engineering processes and the physics-based conventional techniques, along with proficiency in traditional statistics, data mining, artificial intelligence, and machine learning. These methods begin with a data-centric approach to identify issues and develop solutions. While data-driven methods can provide effective solutions for challenging and complex processes that are difficult to define using existing conventional methods, there remains skepticism within the industry regarding their use. This skepticism is closely linked to the delicate and sensitive nature of the processes involved and the handling of data. Proper organization and refinement of data are crucial components of an efficient data-driven process.
Data-driven methods offer significant advantages over conventional methods under certain conditions. However, many industry professionals still have a vague understanding of these methods.[6][7]Oil spills in seas and oceans are a critical source of maritime pollution, driven primarily by human activity and rising oil demand. Their impacts on aquatic ecosystems, wildlife, tourism, aquaculture, and coastal economies are severe and undeniable. Continuous monitoring and prompt intervention are not just important—they are essential for mitigating these environmental crises. Remote monitoring capabilities are indispensable for the protection of marine biodiversity and habitats.The last decade has seen significant advancements in oil spill detection, fueled by increased access to remotely sensed data, enhanced computational power, cloud computing, and cutting-edge machine learning algorithms. Satellite and airborne remote sensing techniques, utilizing a range of sensors such as multispectral, hyperspectral, thermal, and microwave, have proven effective in detecting and estimating the thickness of oil spills. Notably, microwave satellite-based synthetic aperture radar (SAR) stands out for its performance under various weather conditions. The growing reliance on satellite-based multispectral data empowers us to differentiate oil spills from lookalikes, yet the use of ultraviolet and laser fluorosensors remains underutilized.The accuracy of oil spill detection is critically impacted by the similarities between oil spills and other natural or manmade features. Integrating various feature categories—such as statistical, geometric, and texture features—is vital to enhancing classification accuracy. Despite this, many studies still depend on manual feature extraction based on analysts' experience, while only a limited number leverage advanced feature selection techniques, which are essential for improving classification reliability. It is imperative to evaluate the efficiency of features extracted from remote sensing images.

The acquisition of high-quality training samples is a fundamental requirement for effective machine learning classification. The question of how many samples are necessary for dependable results remains unresolved. Collecting accurately labeled samples is a significant challenge due to similarities with lookalikes, which can easily mislead even the most experienced analysts, resulting in unacceptable false positives and negatives in detection efforts. Immediate action is needed to enhance the efficacy of oil spill detection systems for the protection of our marine environments.[7]

CONCLUSIONS:

The findings of this study emphasize the efficacy of utilizing machine learning and artificial intelligence techniques to dynamically automate the welding process, leading to notable advancements in both productivity and safety for large diameter pipes. The integration of these technologies with conventional systems streamlines manual operations and facilitates the precise rotation of the pipe, ensuring accurate alignment of the weld seam. Additionally, the design incorporates a concluding flat portion that ensures synchronization of the seam with high precision, thereby enabling the commencement of Non-Destructive Testing (NDT) without delay. This fully automated approach eliminates the necessity for operators to enter the conveyor area for manual adjustments, thereby significantly enhancing workplace safety.

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