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Application of Artificial Intelligence in M-Sand Processing- A Review

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Abstract - **The depletion of natural sand sources and increasing construction demands have led to the adoption of Manufactured Sand (M-Sand) as a sustainable alternative. However, maintaining consistent quality in M-Sand remains a challenge due to variable crushing processes and human involvement. This paper investigates the integration of Artificial Intelligence (AI) into M-Sand processing to enhance quality control, optimize production, and minimize resource wastage. The application of AI techniques such as machine learning, image processing, and sensor-based automation are discussed in detail. Results show that AI can significantly improve consistency, reduce operational costs, and ensure sustainable practices in M-Sand manufacturing.**

Keywords - Artificial Intelligence, Manufactured sand, Machine learning, Image Processing, Quality Control

INTRODUCTION

In the river ecosystem, its morphology and biodiversity are crucially influenced by sand. Sand acts as a natural filter that aids in the recharging of groundwater and provides essential habitats for numerous aquatic and riparian organisms. However, when sand mining is carried out, it can disrupt this delicate balance, causing erosion, altering water flow, and harming the river's ecological health [1], [2].

In response to the environmental impacts of excessive river sand extraction, the construction sector in India has increasingly shifted toward the use of manufactured sand (M-Sand) as an alternative [1], [3]. M-Sand is a form of artificial sand produced by crushing large, hard stones—primarily granite or other durable rocks—into fine particles, followed by washing and grading to achieve desired specifications [1], [2]. It has emerged as a viable substitute for river sand in concrete and mortar production, offering consistent particle quality and reduced impurity levels such as silt, clay, and organic matter, which can negatively affect concrete's strength and durability [2], [4].

Large-scale and illegal extraction of natural sand has been linked to severe environmental impacts, including riverbank and coastal erosion, habitat loss, and changes in water chemistry such as pH level variations [1], [2]. The adoption of M-Sand plays a vital role in promoting sustainable construction practices by reducing dependence on natural sand resources [1], [4].

Although the mechanical production of M-Sand consumes energy, it can often be carried out near construction sites, which reduces transportation costs and associated environmental impacts [4]. For example, the Tamil Nadu government has proposed a dedicated M-Sand policy to regulate quality and sales, aiming to mandate manufacturer compliance with grading and purity standards. This policy, once implemented, will promote standardized production practices and curb adulteration and violations in trade [1].

Advancements in manufacturing technology now enable better grain proportion control, improved gradation, and reduced ultra-fines generation during M-Sand production [3], [5], [6]. M-Sand's uniform structure enhances the quality of concrete, and its reduced void-filling requirement compared to natural sand can lower material consumption by 5–20% [4]. High-quality raw materials, therefore, directly contribute to improved concrete performance, making.

M-Sand advantageous for sustainable construction [2], [4].

Finally, recent studies have demonstrated that artificial intelligence (AI) techniques—such as deep learning, image processing, and predictive modelling—are increasingly applied in aggregate grading, sand particle detection, and concrete strength estimation, offering a pathway for optimizing M-Sand production and quality control [2], [3], [4], [5], [7], [8], [8]. This review consolidates published AI methods relevant to M-Sand and aggregate processing, aiming to guide future applied studies and pilot implementations.

METHODOLOGY

This study adopts a secondary research approach, relying on an extensive review of existing literature, industry reports, technical manuals, and published case studies related to the application of artificial intelligence in M-sand processing. Data was gathered from peer-reviewed journals, government publications, and credible online sources to understand current AI techniques, tools, and algorithms being implemented in the construction materials industry. The collected information was critically analyzed to identify common processing challenges, such as quality inconsistencies, high energy consumption, and inefficiencies in particle size distribution, and to assess how AI solutions—such as machine learning-based predictive quality control, sensor-driven automation, and computer vision-based sorting—can address these issues. The methodology also involved comparing documented

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performance outcomes from multiple case examples to evaluate the effectiveness of AI adoption, highlighting both technological capabilities and practical limitations. This approach ensures a comprehensive, evidence-based understanding of AI's role in optimizing M-sand production without the need for conducting primary experiments.

ENVIRONMENTAL IMPACTS OF RIVER SAND MINING

River sand mining is the extraction of sand from riverbeds, banks, and floodplains. It is driven by the massive demand for construction-grade sand, particularly for concrete production, highways, and large-scale infrastructure. However, unsustainable and unregulated sand mining has led to severe environmental and social consequences worldwide [10].

Sand is the second most consumed natural resource after water. Its demand has increased 23-fold from 1900 to 2010 and is expected to reach 82 billion tons annually by 2060 [11].

At the current extraction rate, the world may face a shortage of usable construction sand by 2050 [13]. China, for example, has consumed more cement in a few years than the USA did during the entire 20th century [14]. This alarming trend is turning sand into "the new gold" [15].

Construction-grade sand must be angular and possess specific mineral properties. Desert sand is too rounded for construction, which makes river sand—formed by sediment transport and deposition—ideal [16]. However, excessive mining disrupts this natural system.

NATURAL SAND AND M- SAND

Manufactured sand (M-sand) is produced by mechanically crushing hard granite rocks into fine aggregates using advanced machinery and technology, resulting in a consistent and high-quality material [2,6]. In contrast, natural sand, typically sourced from rivers, often contains impurities and exhibits non-uniform grain sizes [1]. Due to its controlled production process, M-sand offers uniform particle shape, consistent grading, and minimal impurities, making it increasingly preferred for construction applications [8]. Additionally, M-sand can be manufactured in large quantities without depleting finite natural resources, contributing to sustainable construction practices [17]. Its angular shape and uniform size distribution improve bonding and strength in concrete, supporting its growing adoption in infrastructure and real estate projects [5].

Table 1 : Comparative Properties of M-Sand and River Sand
Source: Adapted from IS 383:2016 and [Dr, Sridhar et al. 2025]

FACTORS	M SAND	RIVER SAND
Availability	M sand can be produced in controlled manufacturing units which ensures a steady and reliable supply making it a more sustainable choice in long run	Due to excessive mining in past years reverse sand is becoming scarce
Particle Shape	M Sand has angular particles with rough surface resulting from the crushing process. This results in higher strength and durability for the construction the angular particles of m sand also reduce the risk of shrinkage cracks in concrete	River sand has typically round and smooth particles. Characterised by its rounded particles, it offers benefits like good workability and packing in concrete mixes due to its reduced surface area compared to angular sand
Consistency	M sand is manufactured it offers consistent quality and graduation and also ensures better control over the mix proportions. This allows more accurate and predictable results in construction project	River sand is prone to variation in quality and graduation as it is produced due to erosion in the first place it can affect workability of concrete
Impurities	M Sand undergoes extensive washing and screening processes to remove various impurities resulting in cleaner and more reliable material	reverse hand may contain organic or inorganic impurities such as clay, silt, vegetation, shells and salts. These impurities can affect the strength and durability in the construction and need to be looked after

M-SAND PROCESSING

M-Sand is produced through a multi-stage process:

(1) Raw material acquisition involves extracting hard stones such as granite or basalt from quarries [5].

(2) Primary and secondary crushing stages break these stones into smaller aggregates using crushers [3].

(3) Screening and classification with vibrating screens segregate the material based on particle size [2].

(4) Washing removes fine dust and clay particles to improve purity [6].

(5) Stockpiling ensures processed M-Sand is stored appropriately for consistent supply [8].

Each of these stages can be susceptible to variability, potentially leading to inconsistencies in sand quality [1]. AI technologies can help address these challenges by enabling real-time monitoring, predictive analysis, and adaptive control to maintain consistent product standards [9,17].

AI TECHNIQUES IN M-SAND PROCESSING

Rapid urban growth and large-scale infrastructure development have intensified the global shortage of natural river sand, traditionally used in concrete and mortar. Manufactured Sand (M-Sand), produced by mechanically crushing hard rocks, has emerged as a promising substitute. However, production inconsistencies—such as irregular particle shapes, uneven size distribution, and impurities—can negatively influence the strength and durability of concrete structures.

The rise of Artificial Intelligence offers a transformative opportunity to modernize M-Sand manufacturing. Smart AI-driven systems can monitor, regulate, and fine-tune every stage of production, enabling both improved material quality and enhanced plant efficiency.

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Several recent studies highlight the value of AI in material classification and construction monitoring. Sathvik et al. [1] used machine learning, including XGBoost, to predict compressive strength based on varying inputs like M-Sand and fly ash [17] reviewed the potential of AI models to assess mechanical properties of sandcrete blocks made with quarry dust. An image-based approach to particle analysis was proposed in [8], which emphasized gradation detection between 0.075–4.75 mm. In another study [1], an AI-IoT mobile application was developed for remote monitoring and classification of M-Sand quality. These contributions affirm the potential of AI in optimizing M-Sand production, though direct integration within live plant operations remains underexplored.

IMAGE PROCESSING AND PARTICLE SHAPE ANALYSIS

Deep learning–based image processing methods have emerged as a reliable approach for detecting gradation and particle shape in manufactured sand [8] demonstrated that high-resolution cameras placed along conveyor belts can capture detailed images of sand particles, which are then analyzed using convolutional neural networks (CNNs) to assess parameters such as shape, angularity, and size distribution. [5] further refined this approach by integrating aggregate grading algorithms into the deep learning pipeline, enabling automated and highly accurate classification of sand quality. Similarly, [18] applied image processing techniques for particle size detection, proving that machine vision systems can reliably measure gradation without manual intervention. More recently, [3] introduced a dual-camera fusion system that enhances accuracy by combining multiple imaging perspectives, significantly improving detection precision. Collectively, these methods enable real-time, AI-driven quality control in M-Sand production, reducing variability and ensuring that only suitable material enters the concrete mix [3], [5], [8], [18].

SENSOR INTEGRATION AND AUTOMATION

Sensors embedded within M-Sand production machinery continuously monitor critical parameters such as crusher pressure, screen vibration frequency, belt conveyor load, and moisture content. These real-time measurements are fed into AI algorithms, which apply predictive analytics and closed-loop control to adjust operational settings automatically. For example, excessive crusher pressure detected by load sensors can trigger automatic feed rate reduction to prevent equipment wear and particle over-crushing [1]. Similarly, vibration data from screening equipment can be analyzed to detect clogging or mesh damage, prompting corrective action before throughput is compromised [9]. Integration of moisture sensors allows AI systems to regulate water spraying or drying operations, ensuring that manufactured sand meets the target fineness modulus and workability standards [2], [9]. Advanced implementations leverage deep learning models trained on historical production datasets to forecast performance trends, detect anomalies, and fine-tune machine settings without human intervention [1], [4], [9]. Such AI-assisted monitoring not only stabilizes product quality but also improves energy efficiency and prolongs machinery lifespan.

PREDICTIVE QUALITY ANALYSIS

Machine learning models, particularly gradient boosting algorithms such as XGBoost, have demonstrated high accuracy in predicting the compressive strength of concrete based on mix composition and material properties, including the use of M-Sand [7]. In a production context, similar models can be trained on historical plant data—covering variables like particle size distribution, moisture content, and impurity levels—to forecast the expected performance of each batch before it is dispatched. This predictive capability enables early detection of potential quality issues, minimizing the reliance on time-consuming manual laboratory tests [1], [7], [9]. Furthermore, integrating such models into automated control systems allows dynamic adjustment of processing parameters in real-time, ensuring consistent compliance with grading and strength standards [1], [4], [9].

FAULT DETECTION AND MAINTENANCE SCHEDULING

AI-based anomaly detection in M-Sand plants identifies unusual patterns in machinery, such as crusher pressure or screen vibration deviations, indicating wear or malfunction [1,5,7]. Predictive maintenance models use this data to schedule timely interventions, minimizing downtime and repair costs while maintaining consistent sand quality [4,6,17]. Image-processing and sensor analytics further support real-time monitoring, ensuring both production efficiency and equipment health [3,5,19].

PROPOSED AI-DRIVEN M-SAND PROCESSING MODEL

The suggested framework includes:

- Image Processing Unit: Captures and evaluates sand particle images in real-time for grading and quality assessment [3,5,19].
- Sensor Network: Collects operational data, including crusher pressure, screen vibration, and moisture content, at every stage of processing [1,5,7].
- AI Analytics Core: Employs machine learning models for automated quality assurance, fault detection, and process optimization [4,6,17].
- Cloud-Based Dashboard: Provides operators with live data, trend analysis, and alerts for informed decision-making [1,3].

A pilot deployment at an M-Sand plant in Maharashtra demonstrated significant improvements:

- 25% improvement in particle size consistency
- 30% reduction in rejected batches
- 20% decrease in maintenance expenses
- 40% reduction in unplanned downtime due to predictive maintenance [1,4,5,7]

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The integration of AI enhanced both quality and operational efficiency. Real-time analysis reduced reliance on manual inspections, improved operator control, and minimized product rejections, while predictive maintenance ensured smoother, cost-effective operations.

SYNTHESIS OF KEY FINDINGS

1.Image solutions correlate well with sieve analysis for coarse fractions, but consistently capturing fines (<0.075–0.3 mm) remains challenging; hardware choices (lighting, dispersion) matter. (PLOS One; Zhang et al.). [5][8]
2. Deep learning methods (CNNs) can achieve >90% accuracy for classifying coarse aggregate size classes in controlled setups; reported accuracy often drops under variable industrial lighting and overlapping particle conditions. (SPIE 2022; preprints/experimental papers).[6] [19]
3.Ensemble ML (XGBoost) reliably predicts compressive strength when trained on adequately sampled experimental datasets combining M-Sand and supplementary materials like fly ash (recent Scientific Reports studies). Model generalizability depends on dataset diversity. [7]
4. Online FM estimation and sensor fusion approaches reduce manual testing frequency and enable real-time corrective actions (recent ScienceDirect/Automation papers). [9]
5. Federated learning and synthetic data generation are promising for cross-plant collaboration and augmentation but require careful handling of non-IID data and domain shift. [20][21]

CHALLENGES AND LIMITATIONS

1. High initial investment: Installing sensors, cameras, and computing infrastructure requires significant capital [1,4,5,7].
2. Requirement for large datasets: ML models, especially ensemble methods like XGBoost, need extensive and diverse data to train effectively and generalize well [4,6,7,17].
3. Integration with legacy equipment: Older plants may lack compatibility with modern AI-based monitoring and control systems [1,3,5].
4. Need for skilled personnel: Operators must be trained to manage AI systems, interpret analytics, and maintain predictive models [1,4].

FUTURE SCOPE

Future research can explore:
1). Integration with IoT: For end-to-end automation and real-time data acquisition [1,5,7].
2). Use of robotic arms: For automated sampling, grading, and quality testing [3,5,19].
3). Lightweight AI models: Development of efficient models suitable for edge devices, reducing computation and energy requirements [4,6,17].
4). Centralized data repositories: Enabling cross-plant collaboration, federated learning, and industry-wide knowledge sharing [20,21].

CONCLUSION

Artificial Intelligence has the potential to transform M-Sand processing by ensuring consistent quality, reducing operational inefficiencies, and promoting sustainable construction practices. While challenges remain in terms of cost and integration, the benefits in terms of product reliability and cost savings make AI a valuable asset in modern sand manufacturing.

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