Predictive Analysis of Fertilizer Efficiency with Machine Learning

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ABSTRACT

Fertilizers play a key role in agribusiness, both as an essential input for agricultural productivity and as a strategic component in the commercial chain. They provide nutrients that are indispensable for soil correction and crop growth, such as nitrogen, phosphorus, and potassium, allowing the soil to maintain its capacity to sustain crops even after several harvests. It is estimated that about 50% of global food production depends on the use of fertilizers, and in Brazil, these inputs represent approximately 20% of operating costs in agriculture. Given this scenario, the present research proposes a practical approach to predictive analysis of fertilizer efficiency by integrating data science and machine learning techniques into the operational context of agribusiness. The investigation is based on technical indicators defined by experts in agronomic and administrative domains, guiding the analysis of attributes such as particle size distribution, storage unit performance, machinery operation, and process quality control. Exploratory analysis techniques and predictive models were applied to reveal significant statistical correlations between the physical characteristics of fertilizers and their agronomic performance, while also considering operational factors such as production shifts and sample collection consistency. The research seeks to identify efficient production patterns, estimate ideal particle size ranges, and evaluate the performance of machinery and operators, establishing an analytical foundation for strategic decision-making. By combining sector-specific technical knowledge with advanced analytical tools, the findings provide direct support for managers, contributing to process optimization, improved product quality, and increased operational efficiency, thereby reinforcing the relevance of business intelligence applied to agribusiness and promoting decisions based on real data and quantitative evidence. Furthermore, the study identified that storage conditions, mixing equipment, and handling during truck loading exert direct influence on fertilizer particle size throughout the production chain. Results indicate that smaller particle sizes may enhance distribution and agronomic performance; however, when the material reaches pulverization levels, waste, dust-related losses, and reduced commercial value significantly increase. These findings enabled the identification of critical control points capable of minimizing physical degradation, supporting greater particle size uniformity, reduced losses, and improved operational predictability in logistics and industrial flows.

Keywords: data science, fertilizers, agribusiness, data mining, artificial intelligence.

INTRODUCTION

Brazilian agribusiness, responsible for approximately 24.5% of the national Gross Domestic Product (GDP), faces a structural challenge: high dependence on imported fertilizers. Around 85% of the components used to produce fertilizers in the country are sourced from abroad, making national agricultural production sensitive to external factors such as exchange rate fluctuations and geopolitical instabilities. This vulnerability directly affects production costs, undermining the competitiveness of Brazilian products on the global stage (CR 2022). Furthermore, the volatility in input prices for this segment has had a direct impact on the profit margins of rural producers. A survey by the Confederation of Agriculture and Livestock of Brazil (CNA, 2022) found that between 2020 and 2022, fertilizer prices rose by as much as 288%, while prices of major agricultural commodities such as soybeans, corn, and wheat increased by an average of 110% over the same period. This gap highlights the need for more efficient strategies to control and rationally use these inputs. In this context, optimizing fertilizer use efficiency is essential, both to reduce costs and to minimize environmental impacts. As described in a study by the Institute for Applied Economic Research (IPEA, 2022), practices such as fertigation, localized application, and the use of controlled-release fertilizers have been adopted as ways to maximize nutrient uptake and reduce soil losses. These practices indicate a transition toward a more technology-driven and data-based agricultural model. In this regard, predictive analysis of fertilizer efficiency, supported by data science techniques and machine learning, represents a reasonable strategy for guiding intelligent and sustainable decision-making in agribusiness. This approach makes it possible to identify patterns, forecast outcomes, and support managers in the continuous improvement of production and logistics processes, aligning operational efficiency with environmental sustainability.

Despite its importance, gaps remain regarding the predictive capacity for fertilizer performance in the field, particularly with respect to efficiency associated with physical and operational factors such as granulation and storage processes. The absence of intelligent tools capable of interpreting technical and operational data hinders evidence-based decision-making, compromising the optimization of input use.

The research adopted an applied approach based on real data, using data science techniques and machine learning models to identify correlations between granulometric variables and the agronomic efficiency of fertilizers (IKHLAQ 2025). Operational aspects such as production shifts, machinery performance, and collection quality were also analyzed based on metrics provided by specialists. To facilitate the interpretation of results, a Business Intelligence tool was employed, through which interactive dashboards were developed to enable the strategic visualization of data and support decision-making in the sector (LUBY 2025).

It is important to highlight that the research drew upon concepts of Business Intelligence and Data Mining, inherent to the field of Information Systems. It also builds on the fundamentals of Decision Support Systems (DSS), which provide analytical inputs for data-driven management. The use of machine learning techniques integrates with the field of intelligent systems, promoting the automation of analysis and the generation of knowledge from complex operational data (DARZI 2025).

The application of analytical techniques yielded significant statistical results, such as the relationship between the distribution of 2 mm granules and the efficiency of specific equipment and shifts. Inconsistencies in collection and storage processes were also identified, contributing to the construction of predictive indicators capable of guiding operational and commercial decisions with greater precision (IKHLAQ 2025).

From a computational standpoint, the contribution lies in the integration between data science and agroindustrial processes, demonstrating how computational methods can be applied to operational contexts involving unstructured data. The research demonstrates the value of predictive analysis for decision support and expands the field of application of machine learning tools beyond traditional scenarios, contributing practical and scalable solutions for agribusiness (DARZI 2025).

Among the main challenges encountered were the heterogeneity and dispersion of operational data, the limited availability of well-structured historical samples, and the absence of integrated systems for analyzing data according to quality metrics pre-established by specialists. Furthermore, model validation required continuous adjustments due to variations in the technical criteria used in the field, which demanded constant alignment with specialists.

It is also important to note that this research stems from the need to improve input management in agribusiness, particularly regarding technical efficiency and cost-effectiveness in the handling of fertilizers. By proposing intelligent solutions based on real data, the research seeks to meet demands for greater precision and reliability in production, distribution, and commercialization decisions for these inputs.

We highlight that this research sits at the interface among the fields of Information Technology Management, Business Intelligence, and Data Science applied to Agribusiness. The application scenario directly involves the operations of fertilizer companies, distribution centers, and agricultural properties that use inputs, addressing both technical and administrative issues.

PROPOSAL

The research proposal is to develop a predictive analytical model, based on machine learning and operational metrics, that allows managers to anticipate fertilizer efficiency even before its application, taking into account physical and process variables. In doing so, we seek to present an alternative for optimizing logistical, productive, and commercial decisions, increasing the effectiveness of input production management and promoting greater return on investment in the agricultural production chain.

The research makes use of resources such as Business Intelligence (BI) to provide inputs for decision-making in the fertilizer industry, specifically in fertilizer processing and quality control. The research employs artificial intelligence algorithms for data projections when necessary; clustering algorithms are also used to structure the data, with the BI tool responsible for visualizing the transformed data as actionable information.

RELATED WORK

This section presents references that explore machine learning and multivariate analysis; the approaches range from predicting nutritional needs and input recommendations to the use of images and sensors to assess soil characteristics. Methods, algorithms, and practical applications that underpin and contextualize the proposal of this work are highlighted.

The article presented by (WANG 2023) provides a comprehensive review of the use of machine learning algorithms in crop nutritional management practices, focusing on predicting nutritional deficiencies, recommending fertilizer doses, and analyzing spatial variability in soil. Algorithms such as Random Forest, Support Vector Machine (SVM), and neural networks are discussed, along with integration with field sensors and satellite imagery. The authors point out limitations such as the lack of standardized data and the need for integrated public databases. The review highlights that Machine Learning can significantly improve agronomic efficiency when combined with granulometric and multivariate data.

The author (ZHANG 2023) proposes a Deep Learning-based approach to identify distribution patterns of granulated fertilizers. The method uses convolutional networks to analyze high-resolution images of fertilized soils; the system's accuracy is validated in field tests, demonstrating improvements in application uniformity. The study is relevant as it shows how computer vision and Deep Learning can be applied to assess physical characteristics such as granulometry and deposition.

The proposal by (CHEN 2021) analyzes emerging methods and strategies to improve the efficiency of agricultural fertilizer use, including the use of spatial data, remote sensors, and agronomic modeling. Although not centered on machine learning, the article provides methodological context for the adoption of technology in fertilization optimization, including big data approaches and computational simulations that can be integrated with predictive models of fertilizer quality.

The research proposed by (LI 2022) investigates the applicability of different machine learning algorithms (Decision Tree, Support Vector Machines, K-Nearest Neighbors) for recommending optimal input doses such as fertilizers based on historical data on soil, climate, and productivity. The study showed that well-trained supervised models can predict the required nutrient quantities with high accuracy, reducing waste and environmental impacts.

The research presented by (KUMAR 2021) combines spectroscopy (Laser Induced-Breakdown Spectroscopy - LIBS) with multispectral imaging to estimate total nitrogen in agricultural soils. The model uses supervised machine learning (Support Vector Machines and eXtreme Gradient Boosting) trained on spectral data; this technique enables rapid and accurate soil analysis, directly contributing to nitrogen fertilizer recommendations.

The study by (AHMED 2023) proposes an ML-based recommendation system for suggesting fertilizers and biological products; to this end, it uses logistic regression and neural networks to classify and predict the performance of agricultural inputs based on productivity data, pH, granulometry, and soil characteristics. It is highly relevant for multivariate analyses such as Principal Component Analysis (PCA).

The article presented by (KAGABO 2023) develops an agricultural crop recommendation system based on soil analysis, environmental conditions, and ML predictions (Random Forest, eXtreme Gradient Boosting). The authors discuss the influence of nutritional and physical soil factors, encompassing the use of fertilizers and their relationship with input quality.

The study described by (BRUNNER 2023) experimentally evaluates the efficiency of recycled phosphorus fertilizers, correlating physical characteristics such as granulometry and chemical composition with agronomic performance. Laboratory data are subjected to multivariate analysis, with multiple regression used to determine the most relevant attributes.

The article proposed by (SINGH 2022) examines the impact of fertilization practices on chemical and physical soil limitations; this approach includes the collection and analysis of experimental soil data and the simulation of optimal fertilizer application scenarios. It also emphasizes the need to integrate digital tools such as Machine Learning into agronomic decision-making.

The article presented by (REDDY 2021) proposes an intelligent system to predict the ideal quantity of pesticides and fertilizers based on data collected by IoT sensors. This study proposes the use of Decision Trees and Artificial Neural Networks (ANN) to identify application patterns based on climate, soil, and crop type.

METHODOLOGY

The present section describes the procedural methods related to the resources used in our proposal; this refers to the dataset, algorithms, and tools for dashboard creation.

Data Description

The data used in the research is divided into two datasets: the first relates to input materials for fertilizer preparation, and the second refers to the output of the finished product. The input dataset concerns variables associated with input characteristics for quality control regarding grain size and residues as shown in Figure 1;

Figure 1 – Set of sieves for particle size analysis of fertilizers.

The purpose is to verify the quality of the mixture to be performed according to the technical specifications of each destination. It is important to highlight that fertilizers do not have a homogeneous composition, as each region in which they will be used may have different characteristics, meaning the quantity of nutrients used can vary from one region to another. The output dataset refers to post-mixing quality control prior to delivery to the recipient; this control is important to certify that the final product meets the specifications required by each client, respecting the particularities or characteristics of each one. The variables used in the datasets are described below:

Loading (Output)

- 4.75 mm: This refers to the product retained on the 4.75 mm sieve, as shown in Figure 2.

Figure 2 – Sieve 4.75 mm.

- 2 mm: This refers to the product retained on the 2.00 mm sieve, as shown in Figure 3.

Figure 3 – Sieve 2.00 mm.

- 1 mm: This refers to the product retained on the 1.00 mm sieve, as shown in Figure 4.

Figure 4 – Sieve 1.00 mm.

- % 4.75 mm: % retained on sieve
- % 2 mm: % retained on sieve
- % 1 mm: % retained on sieve
- Bottom: This refers to the product that passed through all the sieves and was retained at the bottom, as shown in the image 5.

Figure 5 – Bottom of sieves.

- % Bottom: % residue (dust) retained on sieve
- Mass Weight: weight used to perform the test
- Date: sampling date
- Product: fertilizer name
- Batch:
- Weight (ton): truck weight
- Shift: A, B
- Box/Consumption:

- Equipment (line): mobile bag (hopper) / machinery (mixing)

Unloading (Input)

The output data are the same with the following additions:

- Origin:
- Sample number:

The samples in this study were obtained using the collectors illustrated in Figure 6. After collection, the material passed through a separator (Figure 7) and was transferred to the aforementioned sieves. Subsequently, the assembly was subjected to a vibratory shaker (Figure 8) for a period of 5 to 10 minutes, ensuring the complete screening of the granules to the base of the equipment. Finally, the fertilizers retained in each mesh were weighed and the data recorded in a spreadsheet, consolidating the results for each loading and unloading operation.

Figure 6 – Sample collector.

Figure 7 – Sample separator.

Figure 8 – Vibratory shaker.

Pre-processing

An important step from a methodological standpoint concerns the quality of the data used. Although the datasets were already structured, pre-processing was necessary to address errors related to manual or automatic data entry. These errors include the correction of dates, which may occasionally have incorrect formats, adjustments to numerical values related to decimal precision, and the removal of null values when necessary. These are some of the data cleaning operations required for use both in algorithms and in the construction of dashboards.

Solution Architecture

The architecture proposed in this research focuses on modularity, scalability, and integration between operational data sources and predictive analysis tools. The entire workflow was organized into four main layers: raw data ingestion, structuring in a relational database, analytical processing, and data visualization.

Raw Structured Data

The first stage of the architecture addresses the use of raw operational data obtained from the fertilizer production routine. This data was stored in .csv format files, originating from the quality control and logistics sectors. The data represents a standardized collection of physical and operational variables, such as percentage of retention on sieves (1 mm, 2 mm, 4.75 mm), bottom residue, sample weight, batch, shift, storage box, and production line.

Relational Database

In the next stage, the files were imported into a relational database (PostgreSQL) to ensure structural integrity and facilitate complex queries. During this stage, type conversion procedures were applied, such as transforming text columns into numerical formats or dates. The relational structure made it possible to consolidate data from different sources (input, output, and samples), enabling future integrations with corporate information systems.

Corrected Structured Data (csv)

After the adjustments in the database, the data were exported again in .csv format. At this stage, the data have a standardized and consistent structure for direct use in machine learning algorithms and visualization tools. The corrected data underwent variable normalization, null value treatment, and decimal rounding steps; this preparation was essential to avoid distortions in statistical models and ensure the reproducibility of analyses.

Modeling and Algorithms

The modeling used in this research was built upon a structured dataset derived from real samples of fertilizer production and loading. From this information, machine learning techniques and algorithms were applied with the aim of identifying hidden patterns and promoting a predictive analysis of the operational and physical efficiency of fertilizers. The modeling process began with the definition of target and predictor variables, with emphasis on attributes such as bottom percentage, percentage of granules with a diameter of 2 mm, total weight per batch, equipment line used, production shift, and storage box. These attributes were validated with the support of technical specialists in order to ensure practical relevance in the production chain. The variables were combined to compose metrics that reflect the physical quality of the product and productive efficiency, enabling a quantitative analysis.

Metrics

The definition of the metrics used in the methodology was mapped with the assistance of specialists in the specific area addressed in this research. The metrics are related to quality in fertilizer batch production, using variables contained in the datasets employed. The composition of the metrics is described below:

Bottom percentage by product: this dimension allows the evaluation of the formulation efficiency of each fertilizer regarding the generation of fine residues. Products with high bottom indices indicate lower granulometric stability and greater raw material loss, which directly impacts process quality and cost. This metric is essential for technical adjustments in components or production processes.

Bottom percentage by box/warehouse: reveals possible influences of the storage environment or handling on fertilizer degradation. Significant variations between boxes indicate that structural or operational factors may be contributing to granule breakage, making it necessary to review logistics practices or storage conditions.

Percentage of 2 mm granules by product and by box: measures the percentage of 2 mm granules by product and box, representing an indicator of the physical quality of the fertilizer under different production and storage conditions. The 2 mm granule is considered ideal for its agronomic efficiency and ease of application. The cross-analysis between product and location makes it possible to identify more effective or inconsistent combinations, guiding process improvements.

Estimated 2 mm granules per ton by product: the estimated quantity of 2 mm granules produced per ton of each product. In this regard, it integrates the quality dimension with productivity, offering a quantitative view of the effective yield of ideal granules. Products with a higher proportion of 2 mm granules per ton present greater technical utilization and added value.

Machinery efficiency in the production of 2 mm granules and in bottom reduction: comparatively evaluates the performance of each piece of equipment regarding its capacity to produce ideal granules and reduce bottom generation. The interpretation of this metric supports decisions regarding maintenance, replacement, or reallocation of machinery, with a direct impact on productivity and the quality of final products.

Bottom incidence by production shift: evaluates the adherence of operational teams to technical procedures. Differences between shifts may indicate failures in process execution, equipment calibration, or operator training. This metric supports decisions related to standardization and training.

Relationship between the number of samples collected and the responsible collector: useful for identifying imbalances in the distribution of activities, as well as possible human errors in the sampling process. This metric contributes to controlling data representativeness, assisting in the tracing of inconsistencies and the improvement of the collection protocol.

The results obtained from the dimensions indicated in this research will be validated through feedback from specialist analyses in this agribusiness segment. The evaluation largely depends on a quantitative numerical analysis of the values obtained in each set of metrics; the analyses are carried out individually for each set of metrics, enabling quality monitoring of production for each batch.

Tools and Execution Environment

The architecture used in this research consists of a Python development environment, with the integration of specialized libraries for pre-processing, statistical modeling, and data visualization. The methodological process was structured in a modular fashion, from the treatment of raw data to the generation of interactive dashboards. Pre-processing was conducted through scripts developed in Python, using the Pandas, NumPy, and Scikit-learn libraries for the correction and standardization of the input and output datasets. Cleaning steps were carried out, including:

- Correction of date inconsistencies;
- Normalization of numerical variables with decimal place adjustment;
- Exclusion of records with irreparable null values;
- Conversion of data types to formats suitable for analytical processing.

After pre-processing, the structured data were organized into CSV format files, subsequently migrated to a relational database (PostgreSQL). The migration process included the creation of schemas, adjustment of data types, and definition of keys to ensure referential integrity, facilitating future queries and integrations. The construction of the dashboards uses the Dash framework from the Plotly library, due to its capacity to create interactive web applications with strong graphical performance. The visualizations were designed to enable exploratory analysis oriented toward the diagnosis of fertilizer production quality. The main features implemented are:

- **Scatter Plots with PCA (Principal Component Analysis):** visualization of clusters among production batches, based on the variability of granulometric characteristics.
- **Boxplots by Sieve and Granulometric Ranges:** facilitate the identification of distribution patterns and residue dispersion by product, shift, or equipment.
- **Correlation Heat Maps:** enable the verification of statistical relationships between attributes such as granule dimensions and productive efficiency.
- **Prediction Score Visualizations by Batch:** show in quantitative form the quality classification according to the machine learning models employed.

The dashboard was hosted in a local environment, accessible via web browser, but with an architecture compatible for future migration to web servers, should it be necessary to expand access to multiple users in different locations.

Metrics Used

The metrics defined for this research were developed based on recommendations from specialists in a specific technical area applied to agribusiness, with a focus on fertilizer production. The criteria for each metric are detailed below:

Bottom Percentage by Product: indicates the quantity of fine residue (dust) generated by fertilizer types; this metric is used to assess the physical stability of the product, since high bottom contents indicate raw material loss and a possible reduction in field application quality.

Bottom Percentage by Box/Warehouse: allows analysis of the influence of storage or transport conditions on granulometric degradation; in this regard, significant variations between boxes may indicate operational weaknesses or structural problems.

Percentage of 2 mm Granules by Product and Box: indicates the physical conformity of granules with the size considered ideal for agricultural application, helping to identify granulometric performance across different production lines and storage locations.

Estimated 2 mm Granules per Ton and Product: verifies the production yield of ideal-sized granules in relation to the total volume produced (per ton), integrating quality and productivity.

Machinery Efficiency in the Production of 2 mm Granules and Bottom Reduction: compares performance between pieces of equipment, allowing inference of which production line exhibits greater efficiency in producing ideal granules and lower bottom generation.

Bottom Incidence by Production Shift: indicates performance differences between operational shifts, enabling the identification of variations related to procedures, equipment calibration, or operator training.

Relationship Between Number of Samples Collected and Responsible Collector: an operational metric used to map the representativeness of collected samples and identify possible failures in the sampling protocol.

RESULTS

This section presents the results obtained from the application of the quality metrics defined in the methodology to the dataset related to fertilizer loading. The analyses cover aspects related to granulometric distribution, incidence of fine residues (bottom), efficiency of production equipment, performance by work shift, and variations observed by product and storage environment (box). The tables below detail the average values calculated for each dimension analyzed, enabling a quantitative evaluation of the production process and identifying critical points or opportunities for improvement in the fertilizer production and logistics chain.

From the application of the metrics to the loading dataset, some trends and conclusions can be drawn:

- **Significant Variation in Bottom Percentage Among Products:** products classified as "SAM 20.5" showed higher average bottom values compared to other formulations, indicating greater granulometric fragility or the need for formulation adjustments for this specific product.
- **Influence of Box/Warehouse:** it was observed that certain boxes consistently showed higher bottom values, which may suggest problems in storage or internal handling logistics. Boxes such as box 08 showed a higher bottom percentage, highlighting the need to review logistics practices.
- **2 mm Granule Efficiency:** the average percentage of granules with a 2 mm dimension was satisfactory for most products, with a positive highlight for batches produced on the "MAQUINARIO" lines, which reinforces the operational efficiency of this unit.
- **Differences by Production Shift:** when analyzing data segmented by shift, Shift A showed a lower incidence of bottom residue, suggesting greater adherence to technical procedures or better equipment calibration during this period.
- **Performance by Equipment:** the comparison between different production lines showed that equipment classified under the "MAQUINARIO" line demonstrated better granulometric control, both in the generation of 2 mm granules and in bottom reduction, reinforcing the importance of proper maintenance and calibration.
- **Distribution of Samples by Collector:** the analysis of collection records revealed a concentration of samples among few collectors, which may indicate work overload or inconsistency in sample representativeness. This points to the need to rebalance the distribution of collection activities.

CONCLUSION

This research demonstrated that the integration of data science techniques, machine learning, and Business Intelligence tools represents an effective approach for the predictive analysis of fertilizer efficiency in the agribusiness context. From real operational data, it was possible to identify statistically relevant correlations between physical and operational variables, such as granulometric distribution, equipment used, production shifts, and storage conditions, providing concrete inputs for evidence-based decision-making. The results obtained showed that factors such as storage location (box), production line, and work shift have a direct influence on the granulometric quality of fertilizers, especially regarding the bottom percentage and the proportion of 2 mm granules. Shift A showed a lower incidence of fine residues, while equipment classified under the "MAQUINARIO" line demonstrated better performance both in the production of ideal granules and in bottom reduction, reinforcing the importance of proper maintenance and calibration of machinery.

The metrics defined with the support of technical specialists proved adequate for monitoring production quality, making it possible to identify critical control points capable of minimizing the physical degradation of the product throughout the production chain. The cross-analysis between product, box, and equipment allowed the identification of more effective or inconsistent combinations, guiding process improvements in a quantitative and objective manner.From a computational standpoint, the research contributes by demonstrating how machine learning methods and interactive visualization tools can be applied to agroindustrial contexts with heterogeneous and unstructured operational data. The proposed modular architecture, with layers of ingestion, relational structuring, analytical processing, and visualization via interactive dashboards, proved to be scalable and compatible with future integrations into corporate information systems.

Among the limitations identified, the concentration of samples among few collectors and the heterogeneity in operational data stand out as factors that may compromise sample representativeness and the generalization of predictive models. In this regard, rebalancing the distribution of collection activities and standardizing sampling protocols are recommended as priority actions to improve data reliability in future research. As a perspective for continuity, the expansion of the historical dataset and the incorporation of additional variables, such as climatic conditions and transport logistics data, are suggested as ways to broaden the predictive capacity of the models. The migration of the dashboard to a web environment with multi-user access also represents a natural path to expanding the reach of the solution and promoting its adoption across different links in the production chain.

In summary, by associating technical knowledge from the agronomic sector with advanced analytical tools, the research reinforces the relevance of business intelligence applied to agribusiness, contributing to process optimization, product quality improvement, and increased operational efficiency, promoting decisions grounded in real data and quantitative evidence.

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