DEVELOPING A SMART FACTORY FRAMEWORK A CASE OF CERAMIC TILE MANUFACTURING

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Abstract - This research paper presents a framework for smart factory applications in ceramic manufacturing, harnessing data collection and machine learning algorithms to seamlessly align with the demands of Industry 4.0 and facilitate digital transformation. At its core, the framework is exemplified through the creation of a dynamic web application, consisting of three pivotal modules. The first module encompasses a robust database system for efficient storage and visualization of data from Internet of Things (IoT) devices. The second module orchestrates operational facets, encompassing aggregate planning, predictive maintenance, and quality control. The third module extends its purview to business and finance, adeptly forecasting demand patterns and streamlining payroll management. This multidimensional endeavor is underpinned by overcoming diverse challenges, spanning data governance, interoperability, fortification of information, and scalability.

Key words - Smart factory application; Ceramic tile faults detection; Genetic algorithm; neural network

1. Introduction

In today's tech-driven epoch, industrial evolution hinges on embracing digital transformation. Data's paramount significance cannot be understated – an aggregation of diverse data streams holds immense untapped potential. The Vietnamese ceramic tile industry's ascent to global prominence, with a capacity of 500 million m^2/year, underscores its prowess. Herein lies the essence of digital transformation and the smart factory ethos – an imperative for sustainable growth in the face of escalating rivalry. This trajectory converges with cutting-edge technologies – artificial intelligence, Internet of Things - IoT, and data analytics – validated by scholarly discourse. IoT's real-time data synthesis, expounded by Hozdić et al. [2], underscores informed decision-making across production realms. Fernandez-Carames [3] further amplifies benefits, spotlighting smart factories' role in boosting efficiency via data analysis and control systems. These translate to waste reduction, productivity amplification, and fortified profitability.

In Vietnam, governmental impetus and policies, exemplified by the Vietnam Industry 4.0 Taskforce [9], magnify smart factory integration's momentum. This catalyzes an ecosystem harmonizing tradition and innovation. The metamorphosis of Vietnamese ceramic tile manufacturing embodies progress catalyzed by digital transformation and the smart factory paradigm. Efficiency enhancement, waste curtailment, and competitive ascendancy delineate its multifaceted benefits.

As industries navigate an era of boundless potential, Vietnam's ceramic tile sector stands as a harbinger of digital prowess and transformative excellence.

2. Literature review

Smart factories are revolutionizing the way that products are made, using advanced technologies such as artificial intelligence, the IoT and data analytics to optimize production processes and improve efficiency [1]. These highly digitized and connected factories can collect data from various points in the production process, including machines, products, and materials, and use this data to make informed decisions and improve operations mentioned by Hozdić et al [2].

In 2019, Fernandez-Carames mentioned one of the main benefits of smart factories is increased efficiency. Using data analysis and advanced control systems, manufacturers can optimize production processes in real-time, reducing waste and increasing productivity. This can help save time, reduce costs, and increase profits. Smart factories also offer improved product quality, as data analysis can identify trends and problems in the production process and allow manufacturers to address these issues before they result in defective products [3].

Additionally, the use of advanced technologies such as collaborative robots can help manufacturers adapt to changing conditions and tasks, improving flexibility and responsiveness [4]. Smart factories are enabling manufacturers to improve their competitiveness in the global market in several ways.

By using advanced technologies such as data analytics, machine learning, and the Industrial Internet of Things (IIoT), manufacturers can optimize their operations and make informed decisions. For example, Shariatzadeh et al mentioned that manufacturers can use data from sensors and other connected devices to identify bottlenecks and inefficiencies in their production processes, and then implement changes to improve efficiency and reduce costs [5]. In addition, smart factories can help manufacturers stay updated with the latest technologies and trends, allowing them to quickly adopt new techniques and processes that can give them a competitive advantage. This can be particularly important in fast-changing industries where the ability to quickly adapt and innovate is key to success. Overall, the use of smart factories can help manufacturers reduce costs, improve efficiency, and stay ahead of the competition, enabling them to offer high-quality products at competitive prices and succeed in the global market.

The technologies used in smart factories are diverse and constantly evolving. Artificial intelligence algorithms can be used to analyze data from connected devices and sensors to identify patterns and make predictions, helping manufacturers optimize production processes and make more informed decisions. The IoT connects various devices and sensors throughout the production process, allowing data to be collected and shared in real-time. Data analytics systems analyze this data to identify trends and optimize processes, often using machine learning algorithms to identify patterns and make predictions [6].

Advanced control and automation systems coordinate and optimize production in real-time, using algorithms and sensors to control automated equipment such as robots and conveyor belts. Collaborative robots work alongside humans in the production process and are able to adapt to changing conditions and tasks. Cybersecurity is an important consideration in smart factories to protect against cyber threats. Human-machine interfaces allow humans to interact with machines, such as using touch screens or other user interfaces [7].

While the benefits of smart factories are clear, there are also challenges to the widespread adoption of these technologies. One of the main challenges is a lack of skilled labor – which was presented by Matt et al [8]. As the manufacturing industry shifts towards more advanced technologies, there is a need for workers with specialized skills and training. This requires investment in training and development programs and may also involve retraining existing workers. Another challenge is inadequate infrastructure, including a lack of reliable power and internet connectivity. This can make it difficult for manufacturers to implement and maintain smart factory technologies. Finally, limited access to capital can be a barrier for small and medium-sized manufacturers looking to invest in smart factory technologies. Despite these challenges, the adoption of smart factories is expected to continue to grow as manufacturers seek to improve efficiency, reduce waste, and increase competitiveness. Governments and other organizations can play a role in supporting the adoption of smart factories by providing incentives and support for training and development programs, and by addressing infrastructure and access to capital issues. By addressing these challenges, manufacturers can take advantage of the many benefits that smart factories have to offer.

In Vietnam, the adoption of smart factory technologies is still in the early stages, but the country is making progress in incorporating these technologies into its manufacturing sector. The Vietnamese government has identified the development of a smart manufacturing industry as a key priority and has implemented policies and initiatives to support this goal. For example, the government has established the Vietnam Industry 4.0 Taskforce to oversee the implementation of Industry 4.0 technologies, including those used in smart factories. Additionally, the government has provided financial incentives and support for companies looking to invest in smart factory technologies. However, there are still challenges to the widespread adoption of smart factories in Vietnam, including a lack of skilled labor, inadequate infrastructure, and limited access to capital. Despite these challenges, the Vietnamese manufacturing sector is expected to continue to grow and adopt smart factory technologies in the coming years [9].

Day by day, IoT was a common term that stands for the things that are connected by the Internet but moreover, in 2016 Shariatzadeh mentioned that IoT not only deals with smart connections between physical objects but also with the interaction with different IT tools used within the digital factory, the IoT in manufacturing can be defined as a future where every day physical objects on the shop floor, people and systems (things) are connected by the Internet to build services critical to the manufacturing. Digitalization has improved the production scene and IoT in manufacturing, also known as the Industrial Internet of Things (IIoT), is a step toward transforming conventional factories into smart places. Which has a wide range of applications, including the ability to anticipate problems before they occur, increase profits and customer satisfaction, improve asset management through a connected supply chain, implement operational intelligence, increase quality, production planning and scheduling, etc [10], [11]. According to the article by Mazhar et al [12], employee safety, security, and privacy, machine-to-machine (M2M) automation and IoT blended with Augmented Reality (AR) &Virtual Reality (VR) bring digital and physical worlds closer. The article by Rahman and his partners [13] was using Arduino used to read the sensor with sense the breath then shared to the database via ESP8266 Wi-Fi Module and can be accessed by the patients or registered doctors which purpose the accuracy of the current microcontrollers. Recently, Raspberry Pi - microcontrollers have been introduced with the expectation of being the future of IoT. In the ceramic tiles industry, Boukouvalas the methods including crack and pinhole detectors for plain tiles based on a set of separable line filters, crack detectors for textured tiles based on the Wigner distribution and a novel conjoint spatial-spatial frequency representation of texture, and a color texture tile defect detection algorithm that looks for anomalies in both the chromatic and structural properties of textured tiles [14]. On a variety of tiles with both fake and real faults, automatic inspection techniques have been put into practice and tested. The findings imply that the performance is sufficient to serve as a foundation for an effective commercial visual inspection system. Then Shire showed an automated classification method that helps us to monitor the defects within a very short period and to decide about the recovery process so that the defective tiles may not be mixed with good quality.

In 2020, CNNs achieved remarkable success in many modern image classification tasks. However, it is difficult for users without extensive CNN experience to design the optimal CNN architecture for their image classification problem of interest. The following research by Sun and its partners proposed a method of automatically designing his CNN architecture using genetic algorithms to effectively deal with the task of image classification. The main benefit of the offered method is its "automated" component, which enables users to utilize it without any prior knowledge of CNNs and yet build an appropriate CNN architecture for the given images. The experimental results show that the proposed method outperforms the currently employed automatic CNN architecture design strategies in terms of classification accuracy, parameter counts, and computational resource consumption. The suggested method displays classification accuracy that is very comparable to the best from manually produced, automatically created, and manually tuned CNNs while requiring fewer computational resources [15]. Then in June 2022, Mantau proposed a new approach to using a GA within a YOLOv5 framework for human object detection applied in the Unmanned Aerial Vehicle (UAV) perspective image dataset. The dataset has challenges, such as a small target, the view of the object is from above, and there is an illumination and light effect. The result is that when compared to the original YOLOv5 for Human Detection on Unmanned Aerial Vehicle Perspective, this YOLOv5-based transfer learning approach employing the RGB-TIR dataset and improved by GA may reach greater accuracy [16]. Smart factories use advanced technologies like data analytics, machine learning, and the IIoT to optimize operations, identify inefficiencies, and reduce costs. They also help manufacturers stay current with new technologies and processes, giving them a competitive edge in fast-changing industries. The result is improved efficiency, reduced costs, and the ability to offer high-quality products at competitive prices, allowing manufacturers to succeed in the global market.

3. Research framework

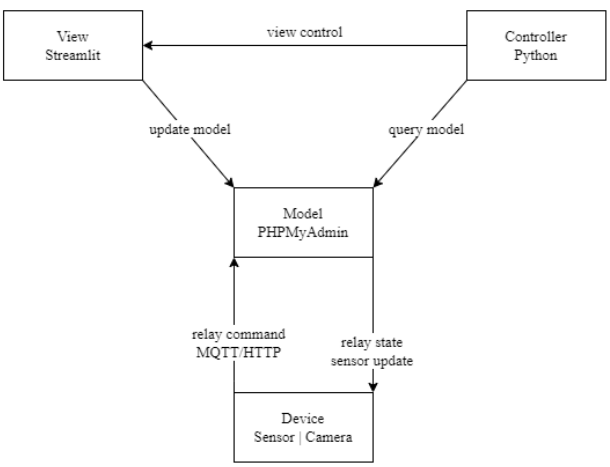

Figure 1. *The Model – View - Controller Pattern*

In this paper, we propose a framework that combines IoT devices, a Relational Database Management System (RDBMS), the Streamlit framework, and machine learning algorithms to address these challenges as in Figure 1. The framework aims to collect and analyze data for defect detection and to improve productivity and quality control in the ceramic tile industry. The Smart Factory application currently has the architecture shown through the MVC model below, including the following components: Model (tables in databases (MySQL) would record information and data transmitted by the Device used to track the required parameters). Controller (these data would be processed by Python and then used as input for models: machine learning or deep learning then the results would be used to support the decision-making process) and View (interactive visualization of data, features, UX, UI is shown through Streamlit - is an open-source Python Library, that makes it easy to create a web app for local testing, the demo of Machine Learning products.

4. Case study

There are 3 modules included: Database Module, Operation Management Module, and Business – Finance Module as in Figure 2. Based on the system specification diagram below, the system is divided into modules with functions serving each department. Decentralized interaction and identification according to the user's department.

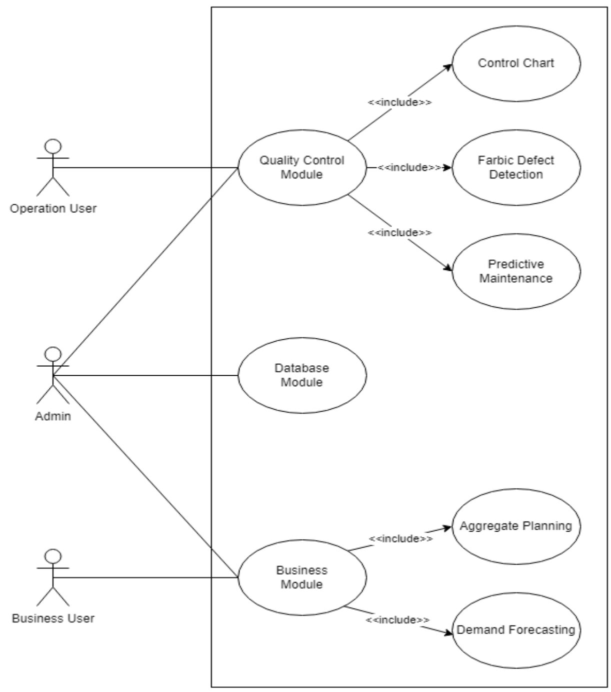

Figure 2. *Use Case Diagram*

4.1. Database module

The Database Module as in Figure 3 is a structured collection of data that is organized and stored in a way that allows for efficient retrieval, manipulation, and analysis. In the context of the Industrial Internet of Things (IIoT), databases are used to store and manage the vast amounts of data generated by connected devices and sensors in manufacturing and other industrial settings.

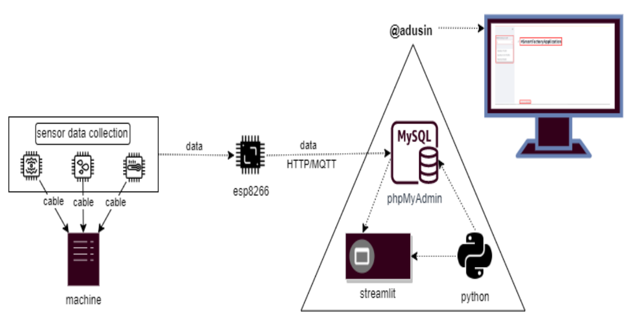

Figure 3. *The suggestion of smart factory framework*

There are several types of DBMSs, including relational database management systems (RDBMS), object-oriented database management systems (OODBMS), and NoSQL database management systems. MySQL is a popular open-source DBMS that is known for its structure and features. PHPMyAdmin is a popular web-based tool that is used to manage MySQL databases, which allows users to create and modify databases, tables, and other database objects. Data can be collected through specialized sensors and sent to the server via MQTT protocol, etc. IoT platforms are used to integrate, manage, and analyze data from connected devices and systems, and are designed to support the integration, management, and analysis of data from connected devices and systems in industrial environments.

4.2. Operation management

The operation management module is a critical part of a smart factory app that manages production, maintenance, and supply chain management. It uses advanced algorithms and tools like process optimization, quality control, predictive maintenance, and supply chain management to optimize workflows, forecast demand and ensure seamless operations. This phase focuses on Quality Control, which includes real-time monitoring of object attributes, machine status, and material defect detection using YOLOv7 and GACNN-optimized CNNs.

4.2.1. Control chart

It's a graphical tool used in statistical process control to monitor and control a process by showing its performance over time. It plots data along with upper and lower control limits calculated based on statistical analysis as in Figure 4. If data points fall outside the limits, it indicates a process issue. Data from EPS8266 was used to create a control chart for real-time monitoring of an observed object, with alarms sent for out-of-control data points to support corrective actions. The chart uses the center line as the average of the data and calculates the upper and lower control limits based on the sample size, estimated std and a multiplier.

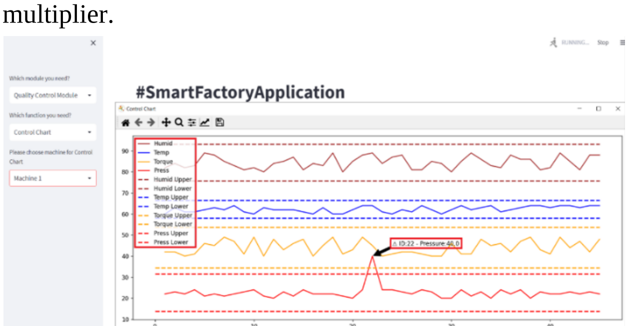

Figure 4. *Control Chart Function*

4.2.2. Monitoring

The monitoring function is essential in an operation management module of a smart factory application as in Figure 5. It involves collecting data from various sources such as sensors and control systems to track the performance of the factory over time. By using these tools, organizations can identify issues and trends in real-time and take corrective action to improve efficiency and effectiveness. The monitoring function also includes automatic on|off modes triggered by out-of-control events and an on|off button in the user interface for reactive machine shutdown.

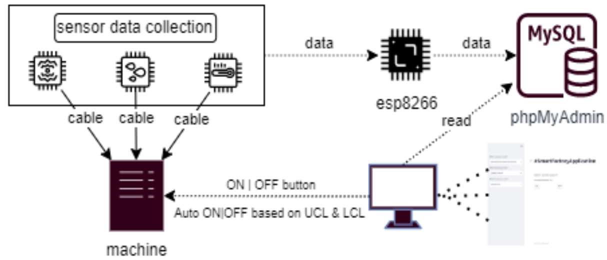

Figure 5. *Monitoring's architecture*

4.2.3. Defect Detection

Defect detection is crucial in ceramic tile manufacturing. Most factories may rely more on visual inspection and testing than automated inspection systems. Advanced technologies such as image processing and artificial intelligence can be used to identify defects in ceramic tiles, and by identifying defects early, manufacturers can take corrective action to improve the quality of the ceramic tiles. The defect types are shown in Table 1.

Table 1. *Defect descriptions*

Defect	Description
BLOB	is a defect, the spot located on the surface, which has a shape like a water drop but erratic, and the radius lasts from some mm to some cm.
SCRATCH	is a defect located on the surface, which is a missing part or multi-part in ceramic tiles with random shapes and an uneven surface, the size of the defect lasts from some mm to some cm.
ECLIPSE	is a defect that often appears on the surface, the discoloration loses the texture of the tile and tends to spread on the surface of the tile, with a size from a few mm to several tens of centimeters.
PINHOLE	is a defect with one or more circular shapes (spots, holes, pits) and black in color, usually located on the surface of the brick, with a radius of several mm.
EDGE	is a defect that loses single or multi-part, usually at the corner (edge) of the tile, with the size from a few cm to several tenths of cm.
CRACK	is a break, crack or cut in the surface of a brick, shaped as single or multi-long slots that divide the brick into two or more but not separate parts, ranging in size from a few mm to several tenths of cm.
DEFECT FREE	is when the surface of the tile is smooth (no cracks, pinholes, eclipses or blobs) and ensures the integrity of the tile (no edges, scratches).

The Ceramic Defects Detection Progress is shown in Figure 6 and Figure 7. Outputs return the probabilities of objects appearing in bounding boxes and probability distribution vectors of classes. The YOLOv7 model is used for training, and the features of the learned object are extracted and saved into the features of the labels. After the evaluation and re-training process, the file weight.pt will be obtained.

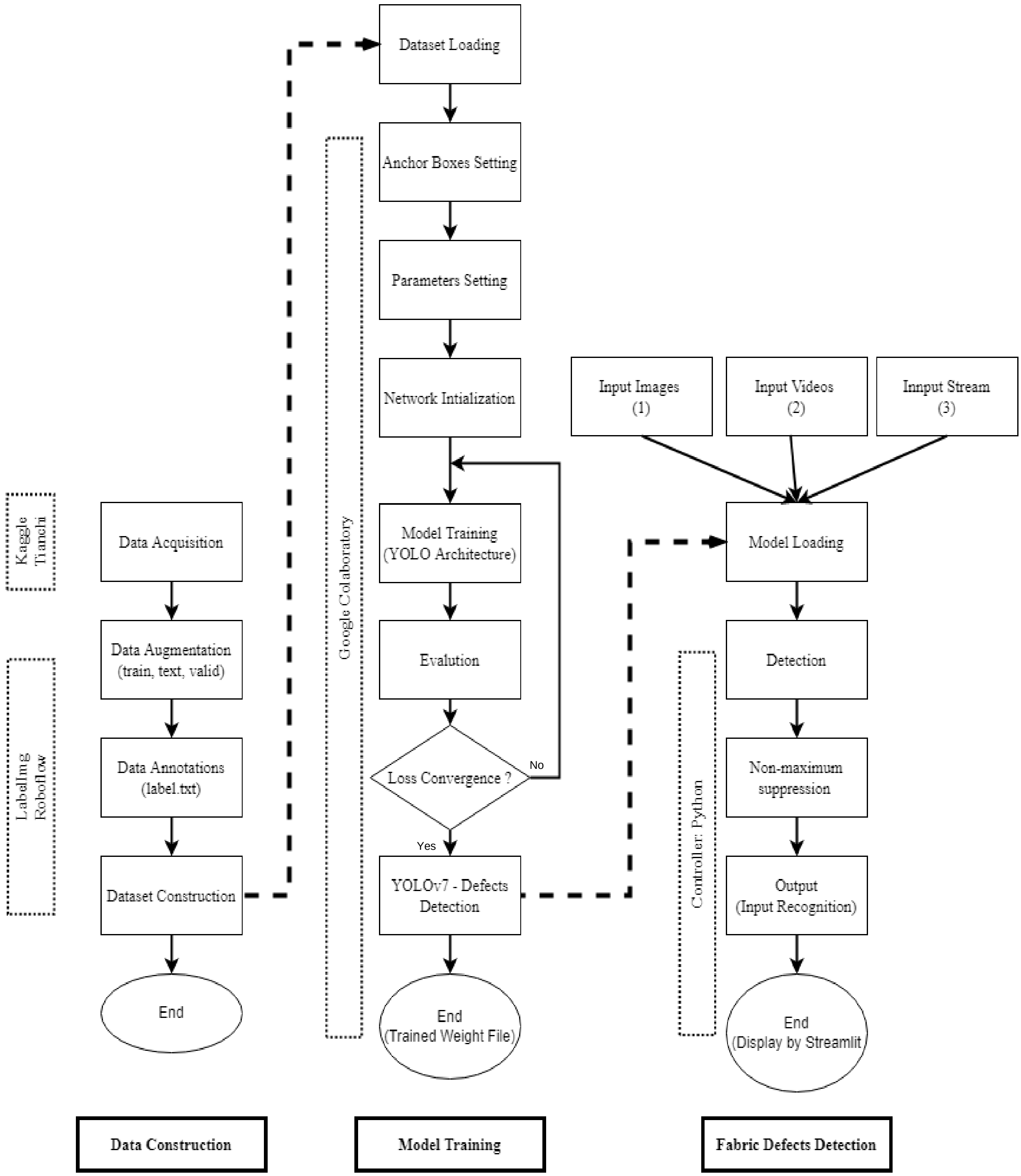

Figure 6. *Ceramic Defects Detection Progress*

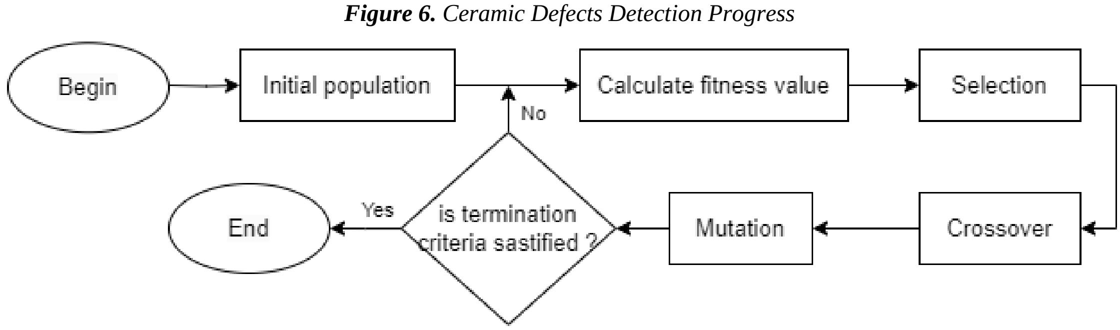

Figure 7. *Genetic Algorithm Progress*

Defects in ceramic tiles can cause a variety of negative consequences for both the manufacturer and the end user, including increased costs, reduced customer satisfaction and reputation, delayed production and delivery, as well as aesthetic, performance, and durability issues. These defects can range from surface defects, shape defects, color defects, finish defects, to quality defects, and it is important to identify and address them early in the manufacturing process to minimize their impact.

The idea is about using GA to optimize the structure of Convolutional Neural Network as in Figure 8. This involves creating an initial population using an encoding routine, using processes of crossover and mutation to produce new offspring, and assessing the best CNN models using a fitness function based on predetermined training and test datasets. A selection procedure is used to choose the chromosomes for the next generation based on fitness ratings, and the process is iterated until the termination condition is satisfied.

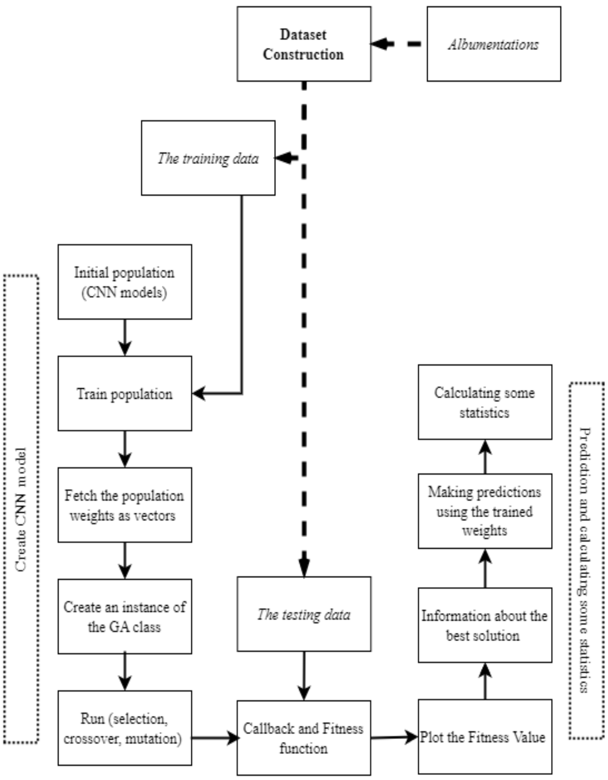

Figure 8. *GACNN Framework*

This method automatically creates the best CNN model using evolutionary algorithms to classify flaws in products based on their surface. The process involves creating an initial population using an encoding routine, crossover & mutation to produce new offspring, and selecting the best models based on fitness ratings.

The passage also includes a comparison of activation functions and an example of a chromosome used in the process. The author suggests that the use of image processing in identifying and analyzing defects in ceramic tiles will continue to evolve and improve in the future, with the potential for increased use of machine learning and advanced sensor imaging systems.

4.2.4. Aggregate Planning

This function focuses on Demand, Productivity, Labor Cost, Inventory Cost, and Relative Factors considered from the sample dataset and then uses genetic algorithms to optimize the Aggregate Planning as in Figure 9. After entering the cost, productivity, and demand data. To plan production with the lowest possible cost, we'll use the "Aggregate Production Planning" tool. Additionally, we'll utilize the "Create" or "Update" function if the value must be added or altered. Once the "Current Data" portion has been verified to be accurate, then choose "Predict" to obtain the plan.

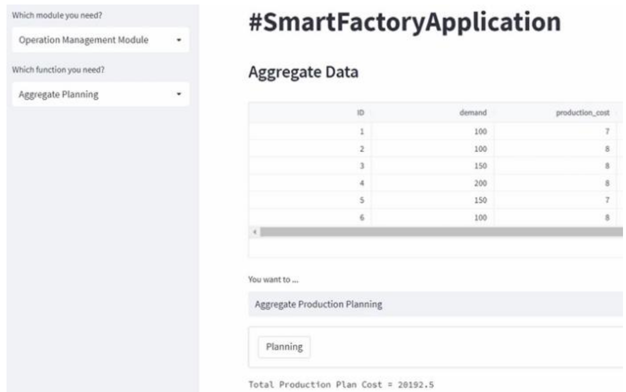

Figure 9. *Aggregate Planning UI*

4.3. Business Module

Due to the beta version, I recommend a straightforward concept, such as importing an excel file into the database to extract specific information about ID, name, number of hours worked, and number of overtime hours, and then calculating the rate per hour based on those numbers as in Figure 10. Net pay is the salary an employee got after deducting all applicable taxes saved back to the database.

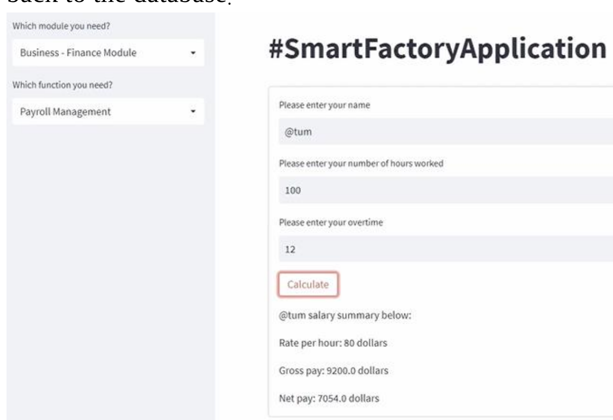

Figure 10. *Payroll UI*

5. Conclusion

The prototype has successfully demonstrated the effectiveness of the framework and has solved some of the industry-specific processes. However, it is evident that the prototype is not yet at the level of being truly smart, but with further upgrades and improvements, it can reach that level. It is also important to acknowledge that implementing this framework is a challenging and long-term process. Nonetheless, the progress made so far is promising and indicates the potential benefits of further development & implementation of the framework in the future.

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