DOI: https://doi.org/10.61762/pjstvol8iss1art001

PLATFORM - A Journal of Science & Technology

Received: 27 February 2025, Revised: 17 March 2025, Accepted: 28 May 2025, Published: 30 June 2025, Publisher: UTP Press, Creative Commons: CC BY 4.0

PREDICTING INJECTION MOULDED PLASTIC FITTINGS QUALITY USING LARGE LANGUAGE MODELS

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ABSTRACT

Maintaining consistent quality in plastic injection moulding is crucial for product functionality and profitability. Traditional quality control methods often rely on manual inspections, are prone to errors and inefficiency, and result in defects and financial losses. This research explores the potential of large language models (LLMs) for real-time, data-driven quality assessments in plastic injection moulding. A Taguchi experiment design was conducted to optimise prompting techniques for an LLM, focusing on the accuracy, reliability, and interpretability of predictions. The experiments systematically evaluated the influence of data augmentation, reasoning methods, temperature settings, and the LLM's personality and role in prediction quality. Results revealed that a specific combination of prompting techniques, including a knowledge base, chain-of-thought reasoning, and a defined LLM personality, significantly improved the LLM's predictive accuracy, consistently yielding more than 75% prediction accuracy. This paper demonstrates the feasibility of using LLMs for real-time quality control in plastic injection moulding, offering a pathway to reduce scrap, enhance quality, and improve production efficiency.

Keywords: *Artificial intelligence, defect prediction, internet of things, prompting techniques, visual inspection, quality control*

INTRODUCTION

Plastic injection moulding is a ubiquitous manufacturing process that produces a vast array of products across diverse industries. The process, however, is susceptible to various defects, such as short shots, flashes, and burn marks, arising from fluctuations in material properties, processing parameters, and mould design [1]. Traditional quality control methods, which often rely on visual inspections and manual measurements, are inefficient and prone to human error, resulting in potential product defects, safety concerns, and financial losses due to scrap and rework [2]. Recent advances in artificial intelligence, particularly large language models (LLMs), offer a transformative solution [3]. LLMs, trained on massive datasets of text and code, possess remarkable capabilities in understanding and generating human language, making them suitable for analysing complex data patterns and providing human-interpretable insights [4]-[5]. Integrating LLMs into quality control systems holds immense potential for real-time, data-driven assessments, enabling proactive defect prevention and process optimisation. A notable gap is the lack of studies on how LLMs can be effectively integrated into control systems for injection moulding processes.

This paper presents the design and development of an LLM-based quality control system for injection moulded plastic fittings. The primary objective is to optimise the prompting techniques for the LLM to maximise the accuracy, reliability, and interpretability of quality predictions. Furthermore, the study aims to design an interactive system that allows operators to query the LLM for real-time insights and troubleshooting and to create a comprehensive framework for effectively integrating LLMs into quality control processes. The work encompasses data acquisition and processing, web interface development, optimisation of prompting techniques through the Taguchi method, and the creation of an interactive LLM program simulation.

LITERATURE BACKGROUND AND GAP ANALYSIS

The plastic injection moulding industry faces the critical challenge of ensuring the consistent quality of manufactured parts. While traditional methods, such as visual inspection and manual measurements, have been the cornerstone of quality control, their inherent limitations in terms of efficiency, accuracy, and adaptability become more apparent in light of production demands [2],[6]. Visual inspection, despite its apparent simplicity, is inherently subjective and prone to human error [2]. Research highlights significant variations in defect detection rates among inspectors, exposing the unreliability of relying solely on human observation [7]. This subjectivity, coupled with the limitations of manual measurements using tools like callipers and micrometres, hinders the accuracy and repeatability of quality assessments, especially for complex geometries [6]-[7]. The reliance on human inspections has, in recent times, been unable to keep pace with the speed and automation of modern production lines. Hassan and Diab [2] aptly capture this struggle, emphasising the difficulty of integrating manual inspection and measurements into automated processes that can run nonstop with minimal human effort. Thus, quality assessment becomes a significant bottleneck in the system if carried out frequently. This incompatibility hinders real-time quality control and risks, allowing defects to slip through undetected, potentially affecting downstream processes and product integrity.

Recognising these shortcomings, the field of quality control has adopted modern technologies, including Artificial Intelligence (AI) and the Internet of Things (IoT). Early research demonstrated the potential of computational tools, such as neural networks and genetic algorithms, for optimising process parameters, paving the way for AI integration in plastic injection moulding [8]-[9]. Shen et al. [8] further advanced this progress by demonstrating how AI effectively predicts and controls critical factors, such as melt temperature and injection pressure. This shift towards preventive quality control was further propelled by the emergence of Industry 4.0 and the use of IoT devices. Aminabadi et al. [10] highlight the power of in-line AI quality control using IoT, where AI-powered sensors and cameras enable real-time defect detection and process adjustments directly on the production line. This continuous feedback loop minimises scrap rates and ensures consistent product quality. Moreover, the research emphasises the development of AI-driven optimisation tools that continuously analyse data from sensors and production history, automatically adjusting process parameters to adapt to changing conditions [11].

However, even these advanced systems have their limitations. The complex nature of the injection moulding process, with its multitude of interacting variables [8],[10]. It necessitates extensive data collection and processing for training robust AI models that can often not run on the production line as an integrated system [11]. Integrating AI solutions into existing production lines can be disruptive and costly, requiring significant infrastructure adjustments and workforce training [5]. Amidst these advancements, LLMs are emerging as powerful tools with transformative potential for quality control. LLMs have demonstrated impressive capabilities across various domains, including natural language processing, code generation, and even creative writing [12]-[13]. Their ability to process and understand complex information makes them suitable for data analysis and decision-making tasks, paving the way for innovative applications in industrial settings. LLMs' strength lies in their ability to process and analyse vast amounts of data, thus identifying patterns and anomalies that might elude traditional methods. This capability allows them to generate predictions, provide detailed explanations for those predictions, and even suggest corrective actions, bridging the gap between data analysis and actionable insights [14].

The effectiveness of LLMs relies heavily on the art of "prompting", crafting specific instructions or questions that guide the model toward the desired output. Researchers are actively exploring various prompting techniques to maximise the accuracy, reliability, and interpretability of responses from LLMs. Research on LLM prompting techniques highlights the significance of carefully crafting prompts to guide the LLM's reasoning and output [13]. Techniques such as few-shot learning, chain-of-thought prompting, and personality/role assignment have shown promising results in enhancing LLM performance and interpretability [15]-[16]. Zero-shot prompting leverages the ability of LLMs to generate text without explicit training on a specific task [13]. Few-shot prompting involves providing the model with limited examples, enabling it to learn and generalize to new instances [15],[17]. Chain-of-thought prompting encourages the LLM to break down complex tasks into smaller steps, making its reasoning process more transparent [18]. Automatic prompt engineering leverages machine learning algorithms to optimize prompts, reducing reliance on manual crafting [16],[18]. Despite their promise, LLMs are not without limitations. They are known to generate inaccurate information that appears plausible; this is often referred to as "hallucinations" [19]. There are also noted inherent biases that LLMs exhibit, which are attributed mainly to the training data used to train them [20]. Their immense size and complexity often lead to challenges in data efficiency, interpretability, and mitigating societal biases [21]. Addressing these challenges is crucial for the responsible and effective integration of LLMs in quality control.

MATERIALS AND METHODS

This research employed a multi-faceted approach to develop and assess the LLM-based quality control system for plastic injection moulding. The methodology hinged on the Taguchi experimental design framework to identify optimal prompting techniques for the LLM. This involved carefully selecting control factors and their corresponding levels, which are integrated into a structured series of experiments outlined by an orthogonal array.

LLM Selection

Central to this evaluation was the choice of the LLM itself. A weighted Pugh Matrix was employed to compare different LLMs based on criteria such as text and image classification accuracy, ease of integration, and cost. This structured approach ensured the selection of the most suitable LLM for this specific application, ultimately contributing to the reliability and effectiveness of the entire quality control system.

The system design is illustrated using a sequence diagram (Figure 1), which demonstrates the interactions between system objects. This includes the communication between sensors, the microcontroller, and the cloud platform during data acquisition and transmission. It also shows the communication between the LLM Quality Management System.

Table 1 LLM selection: Weighted Pugh matrix

Criteria	4ght	LLM 1 (LLaMDA)	LLM 2 (Gemini Pro)	LLM 3 (ChatGPT)	Decision
Text Classification Accuracy	0.4	3	5	3	No
Image Classification Accuracy	0.3	5	3	5	No
Ease of Integration	0.2	3	5	1	No
Cost	0.1	1	1	3	Yes
Total Weighted Score		3.4	4	3.2	Gemini Pro

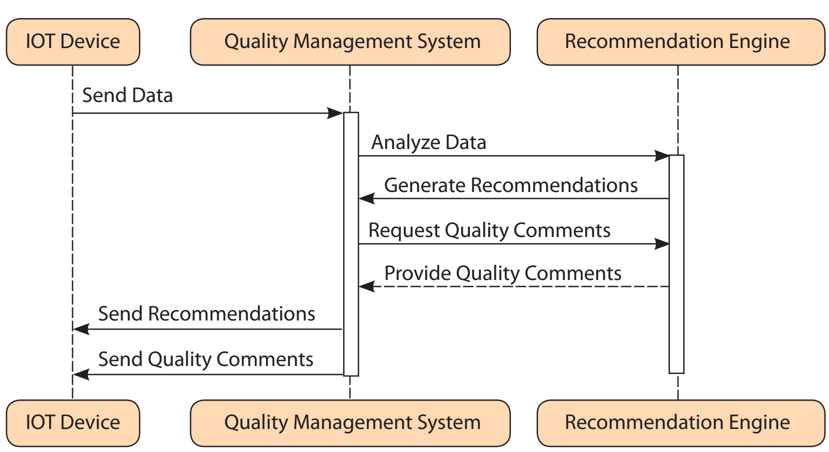

Figure 1 LLM Quality Management System sequence diagram

Experimental Setup

In order to predict quality fittings using an LLM, it is important to generate the most effective prompt. To empirically determine the optimal prompt, this paper employed Taguchi experiments. The Taguchi method provides a systematic framework for optimizing processes and systems [22]. By strategically evaluating a limited set of experimental conditions, the method efficiently identifies the key factors influencing a desired outcome and determines the optimal settings for those factors. The Taguchi method's emphasis on minimising variability and maximising robustness aligns perfectly with the goal of developing a reliable and effective LLM-based quality control system. In this work, the generated prompts were then fed to the LLM, and their performance was rigorously evaluated based on metrics such as accuracy, reliability, and explainability. This iterative process enabled a systematic analysis of how different prompting techniques affected the LLM's ability to detect defects effectively and assess the quality of moulded parts. The method used is illustrated in Figure 2.

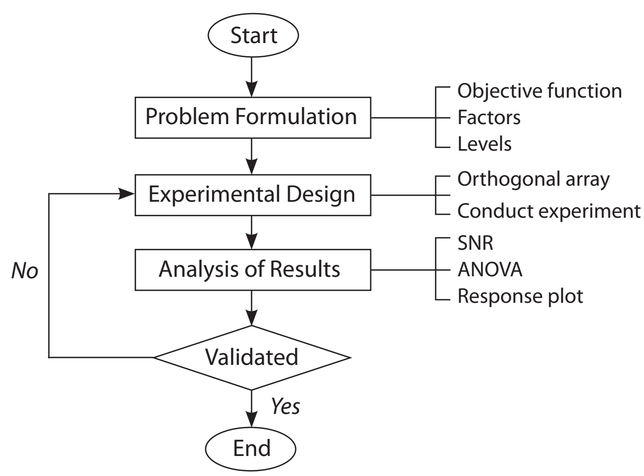

Figure 2 Taguchi methodology

The core of this experiment was to predict the quality of injected fittings, which involved generating specific prompts based on the Taguchi array, each incorporating a unique combination of prompting techniques. The investigation into prompting techniques includes the influence of four control factors on the LLM's quality prediction performance. An intensive literature review was conducted to select the best prompting techniques. The chosen techniques were based on the type of LLM used, the number of citations for the research paper, and the credibility of the experimental methods used, as supported by other researchers. The prompting factors, identified through a literature analysis, are presented in Table 2. These factors, each with three levels, were data augmentation, reasoning method, temperature setting, and personality.

Table 2 Prompting factors

Data Augmentation	None (Zero-Shot)	5 examples (Few-Shot)	25 examples (Knowledge Base)
Reasoning Method	None	Chain-of-Thought	Tree-of-Thought
Temperature Setting	0	0.5	1
Personality/ Role	None	Role Only	Personality + Role

A Taguchi L9 orthogonal array was employed to set up the experimental plan for investigating the influence of four control factors on the LLM's quality prediction performance (Table 3). Prompt development was thus directly informed by the Taguchi experiment design. Each prompt was constructed following a predefined structure, ensuring the systematic incorporation of control factors at their designated levels. This helps to isolate the impact of each prompting technique on the LLM's performance. The effectiveness of these prompts was then rigorously assessed based on two primary metrics: accuracy and reliability. Accuracy measured the LLM's ability to correctly classify the quality of moulded parts, represented as the percentage of correct classifications. On the other hand, reliability assessed the consistency of the LLM's predictions. This involved presenting the LLM with the same input multiple times and evaluating the consistency of its output, providing insights into the stability and dependability of its quality assessments.

Sensor-Based LLM Quality Control System Development and Mechanism

The quality control system, built to mimic existing quality control systems, utilises an IoT-based system that leverages sensor data and image data to predict and determine the quality of produced plastic fittings. The sensor locations are shown in Figure 3. This system is not involved in the process control variables, as this is assumed to be the working of a separate system and is not the focus of this paper. The paper's primary focus is to determine if an LLM can assist in making an LLM

Table 3 Taguchi L9 orthogonal array

Run	A (Data Augmentation)	B (Reasoning Method)	C (Temperature)	D (Personality/Role)
1	1 (Zero-Shot)	1 (None)	1 (0)	1 (None)
2	1 (Zero-Shot)	2 (Chain-of-Thought)	2 (0.5)	2 (Role Only)
3	1 (Zero-Shot)	3 (Tree-of-Thought)	3 (1)	3 (Personality + Role)
4	2 (Few-Shot)	1 (None)	2 (0.5)	3 (Personality + Role)
5	2 (Few-Shot)	2 (Chain-of-Thought)	3 (1)	1 (None)
6	2 (Few-Shot)	3 (Tree-of-Thought)	1 (0)	2 (Role Only)
7	3 (Knowledge Base)	1 (None)	3 (1)	2 (Role Only)
8	3 (Knowledge Base)	2 (Chain-of-Thought)	1 (0)	3 (Personality + Role)
9	3 (Knowledge Base)	3 (Tree-of-Thought)	2 (0.5)	1 (None)

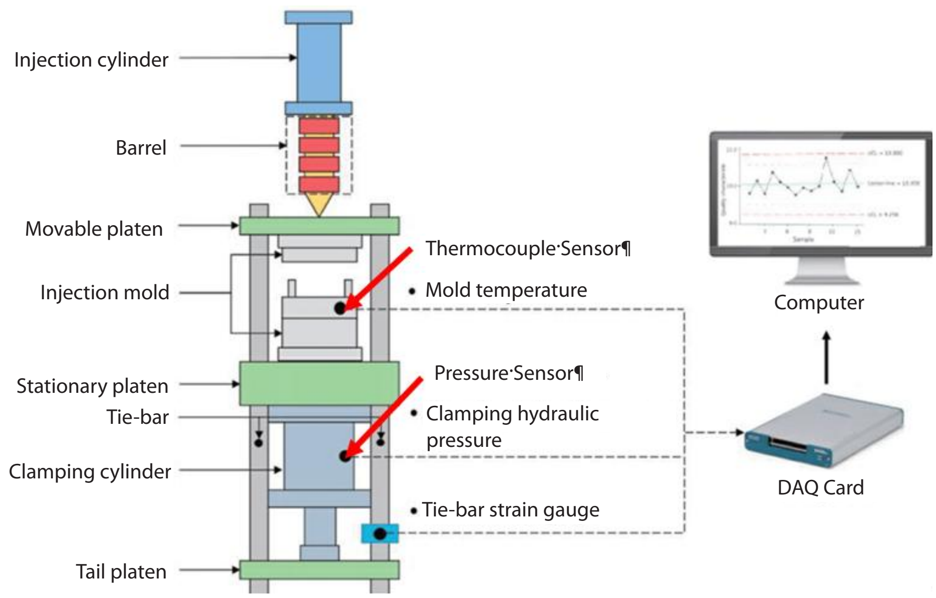

Figure 3 Sensor locations

that can detect divisions in quality based on sensor data readings. Against this backdrop, the authors do not focus on developing a unique quality control system; instead, they illustrate the basics using an Arduino system with sensors to collect temperature, pressure, and cycle time data. The Arduino system communicates with a server and sends information to an SQLite database via HTTP POST, following the logic shown in Figure 4. The following algorithm illustrates the data acquisition

Algorithm DataAcquisitionAndPreprocessing:
Input: Sensor readings (temperature, pressure, cycle time) from Arduino
Output: Preprocessed sensor data ready for LLM input

1. Establish connection with Arduino via serial communication or HTTP
2. Read sensor data:
   temperature = readTemperatureSensor()
   pressure = readPressureSensor()
   cycleTime = readCycleTimeSensor()
3. Validate sensor data:
   If temperature, pressure, or cycleTime is NULL or invalid:
      Log error message
      Return error (or default values)

4. Normalize sensor data (Min-Max scaling to [0, 1] range):
   temperature_normalized = (temperature - min_temperature) / (max_temperature - min_temperature)
   pressure_normalized = (pressure - min_pressure) / (max_pressure - min_pressure)

```
    cycleTime_normalized = (cycleTime - min_cycleTime)
    / (max_cycleTime - min_cycleTime)

5. Package data:
    sensor_data = {
        "temperature": temperature_normalized,
        "pressure": pressure_normalized,
        "cycleTime": cycleTime_normalized
    }
6. Store raw and normalized data into SQLite database

7. Return sensor_data
```

An interactive web application was developed to showcase the practical implementation of the LLM-based quality control system. This application allows operators to input simulated or real-time sensor data from the injection moulding machine and receive instant quality predictions from the LLM, along with explanations, troubleshooting suggestions, and system monitoring capabilities. The Python-based web application, utilising the Bottle framework, displays sensor data and enables users to query the LLM – Gemini Pro – via the Google generative AI API. The LLM analyses the sensor data and provides a quality classification (high, medium, or low) with a confidence score, reasoning, and optional recommendations. In markdown format, the LLM response is converted to HTML for display on the web application using marked.js.

This paper also noted the use of visual inspection in the quality control system and thus uses LLMs for image-based defect detection in plastic injection moulding. The LLM analyses images and provides a description, identifies defects (for example, short shots, burn marks, sink marks), and explains their likely causes, considering factors such as processing parameters, mould design, and material properties. The system aims to improve efficiency, scalability, and consistency in visual inspection. It operates similarly to the sensor-based system, as illustrated in Figure 4, but utilises a distinct prompt.

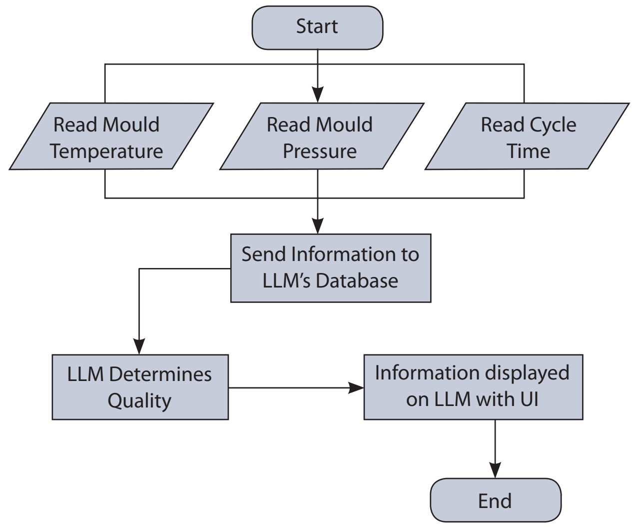

Figure 4 Sensor-based LLM quality control system logic

RESULTS AND DISCUSSION

In this research, prompting techniques were developed and fed into an LLM that predicts the quality of injection moulding products. Taguchi's experiments paved the way for identifying the optimal prompt techniques for generating a high-quality LLM-based quality monitoring system. The experiment investigated the influence of various control factors on the system's effectiveness, aiming to establish a set of prompts that maximise its monitoring capabilities. The findings presented here provide valuable insights for tailoring prompt design to LLM-powered monitoring systems, ultimately leading to improved performance and accuracy. The main outputs of the research were the correct prompting technique, LLM predictions based on injection moulding parameters, and LLM-based quality prediction using images of defects.

Prompting Technique

The Taguchi experiment results (Table 4) revealed the influence of prompting techniques on the LLM's quality prediction performance. The optimal prompt configuration, achieving the highest average accuracy (75%) and reliability, incorporated the following:

1. Knowledge Base: Augmenting the LLM with a knowledge base of 25 example cases significantly improved its understanding of the relationship between injection moulding parameters and quality outcomes.
2. Chain-of-Thought Reasoning: Guiding the LLM to explain its reasoning process step-by-step enhanced the interpretability of its predictions and contributed to increased accuracy.
3. Personality/Role: Defining a clear personality and role for the LLM ("a professional quality control system") improved the consistency and focus of its responses.
4. Temperature Setting: A low-temperature setting (0) ensured that the LLM's responses remained

Table 4 Taguchi experiment results: average accuracy and reliability scores

Factors					Result (5 Times) (Accuracy * Reliability)	Result (5 Times) (Accuracy * Reliability)
Run	A	B	C	D	X_1	X_2
1	1	1	1	1	0.4095	0.3956
2	1	2	2	2	0.6237	0.6311
3	1	3	3	3	0.5376	0.5445
4	2	1	2	3	0.4556	0.44
5	2	2	3	1	0.656	0.677
6	2	3	1	2	0.6715	0.682
7	3	1	3	2	0.7134	0.7091
8	3	2	1	3	0.76	0.7564
9	3	3	2	1	0.7254	0.7318

grounded in the provided data, reducing the likelihood of hallucinations or irrelevant outputs.

Moulding Parameters Based on LLM Predictions

The key parameters assessed were mould temperature, mould pressure, and part-cycle time. In the first instance of using simulated data, operators can utilise it to test system parameters and assess the impact of those settings on the output quality. The User Interface (UI) for the system is shown in Figure 5.

The system can also be used with IoT-based data, as shown in Figure 6, from sensors connected to the injection moulding machine. This includes the DS1800 temperature sensor, the BMP180 pressure sensor, and a button-operated oscillating timer. These values are sent via an API to the server and stored in a database before being retrieved by the system to determine the quality. The algorithm used to determine the output is shown as:

```
Algorithm LLMInteractionAndPrediction:
    Input: Preprocessed sensor data (sensor_data), LLM
    model (Gemini Pro)
    Output: Quality classification, confidence score,
    reasoning, recommendations

1.  Construct LLM prompt:
    prompt = createPrompt(sensor_data, prompt_template)

2.  Query LLM:
    LLM_response = queryLLM(Gemini Pro, prompt) //
    Using Google Generative AI API

3.  Parse LLM response:
    quality_classification = extractQualityClassification
    (LLM_response)
    confidence_score = extractConfidenceScore(LLM_response)
    reasoning = extractReasoning(LLM_response)
    recommendations = extractRecommendations
    (LLM_response)

4.  If quality_classification or confidence_score are
    NULL or invalid:
    Log error message: "LLM response parsing failed"
    Return error

5.  Format Output:
    formatted_output = {
        "quality_classification": quality_classification,
        "confidence_score": confidence_score,
        "reasoning": reasoning,
        "recommendations": recommendations
    }

6.  Return formatted_output
```

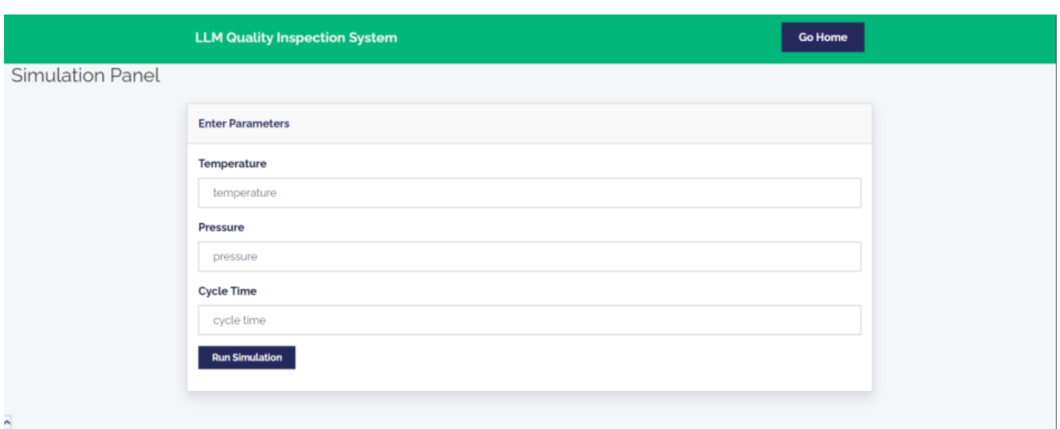

Figure 5 Simulated data panel based on operator input

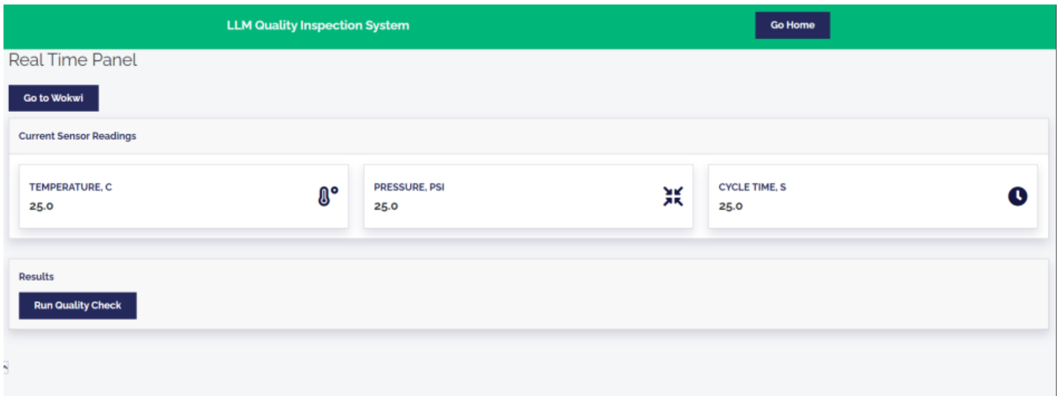

Figure 6 Real-time panel based on IoT data

The LLM system was able to provide a response that included the classification, reasoning, recommendations, and additional considerations, as shown in Figure 7. The LLM system first displays the output classification and predicted quality and then further explains the reasoning. This process is designed to enable a skilled human to identify if and where the AI made an error. Additionally, the response includes the possible causes and proposed recommendations to fix the issue.

Image-Based Defect Detection Using LLM

The LLM system was also used for visual inspection based on image uploads to the server. Figure 8 illustrates the UI for the system.

The output of the image-based defect detection system was based on the following structured output, as shown in the algorithm.

Algorithm ImageAnalysisLLM:
  Input: Image Data, Instruction String
  Output: JSON String

1. prompt = CreateImageAnalysisPrompt(image, instruction)
2. response = QueryLLM(Gemini Pro, prompt)
3. parsed_response = ParseJSON(response)
4. **return** parsed_response

where parsed_response = {
  "description": "...",

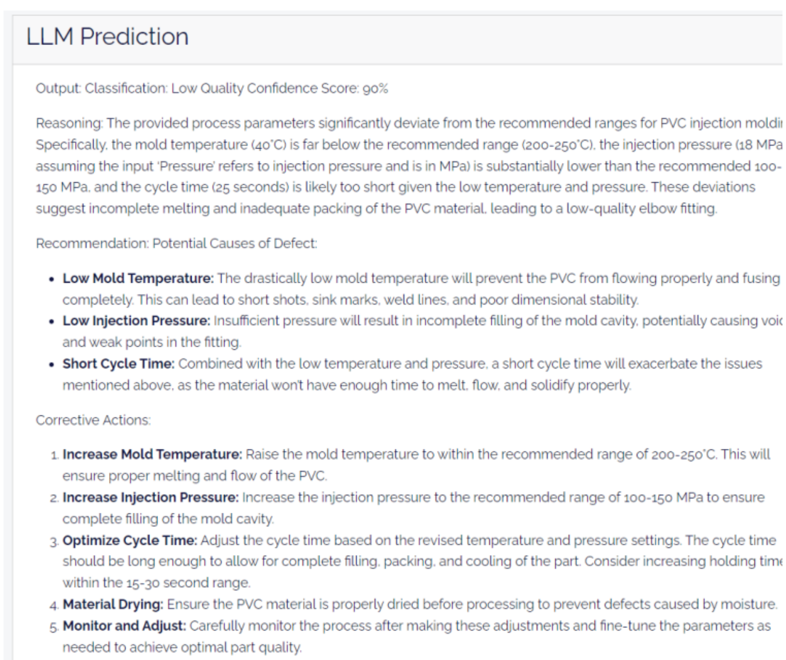

Figure 7 LLM outputs for predictions based on mould parameters

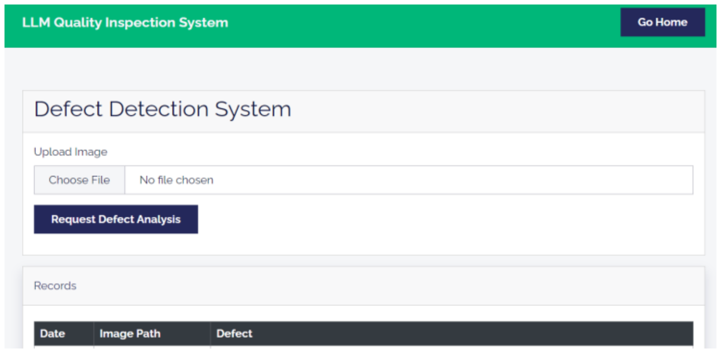

Figure 8 Image-based defect detector

```
    "Defect Indetification": "...",
    "Defect Explanation": "..."
}
```

It followed the structure and provided the required output when given the image shown in Table 5.

1. Description
2. Defect Identification
3. Defect Explanation

CONCLUSION

This research demonstrates the effectiveness of employing large language models (LLMs) for real-time quality control in injection-moulded plastic fittings. A systematic Taguchi experiment identified optimal prompting techniques, significantly improving the LLM's predictive accuracy, reliability, and interpretability. The development of an interactive web application showcased the practical implementation of the LLM-based system, offering a user-friendly tool for operators to leverage the power of LLM-driven quality assessments. The main conclusion of this paper is that LLMs accurately predict the quality of injection moulding products in terms of dimensional and form accuracy. Results revealed that a specific combination of prompting techniques, including a knowledge base, chain-of-thought reasoning, and a defined LLM personality, significantly improved the LLM's predictive

Table 5 Image based LLM output

Testing Data	
Input Image	Output
	1. Description: The image shows a greenish incomplete (short) coupling. 2. Defect Identification: A short shot is evident in the partially filled couplings. 3. Defect Explanation: The short shot likely occurred due to incomplete filling of the mould cavity. The factors are caused by inconsistent wall thickness in the mould design, uneven cooling across different sections of the part, or using a material with low melting properties.
	1. Description: The image shows a clear coupling with a smooth, greenish surface. 2. Defect Identification: Burn marks are visible as brown discolouration around the surface of the coupling. 3. Defect Explanation: The burn marks likely occurred due to excessive heat generated during the injection process. This could be caused by factors such as high melt temperature, improper venting in the mould, or excessive holding time, which kept the molten plastic in contact with the mould for too long.

accuracy and consistency to 75% compared to 38% produced when the LLM was prompted with no reasoning technique, examples or personality. This paper demonstrates the feasibility of using LLMs for real-time quality control in plastic injection moulding, offering a pathway to reduce scrap, enhance quality, and improve production efficiency.

ACKNOWLEDGEMENT

The authors express gratitude to the Department of Industrial and Manufacturing Engineering at the National University of Science and Technology, Zimbabwe, for the support availed to conduct this research.

REFERENCES

[1] A. Mourya, A. Nanda, K. Parashar, Sushant, and R. Kumar, "An explanatory study on defects in plastic moulding parts caused by machine parameters in injection moulding process," *Materials Today: Proceedings*, vol. 78, pp. 656-661, 2022.

[2] M.H. Hassan and S.L. Diab, "Visual inspection of products with geometrical quality characteristics of known tolerances," *Ain Shams Eng. J*, vol. 1, pp. 79-84, Sept. 2010.

[3] A. M. Ardestani, G. Azamirad, Y. Shokrollahi,... G. Tosello, "Application of Machine Learning for Prediction and Process Optimisation-Case Study of Blush Defect in Plastic Injection Moulding," *Applied Sciences*, vol. 13, p. 2617, 17 Feb. 2023.

[4] S. Sarsa, P. Denny, A. Hellas, and J. Leinonen, "Automatic Generation of Programming Exercises and Code Explanations Using Large Language Models," in *Proceedings of the 2022 ACM Conference on International Computing Education Research*, 2022.

[5] F.F. Xu, U. Alon, G. Neubig, and V.J. Hellendoorn, "A systematic evaluation of large language models of code," in *Proceedings of the 6th ACM SIGPLAN International Symposium on Machine Programming*, 2022.

[6] A. Konig, P. Windirsch, M. Gasteier, and M. Glesner, "Visual inspection in industrial manufacturing," *IEEE Micro*, vol. 15, pp. 26-31, June 1995.

[7] S. Yeralan and J.A. Ventura, "Computerised roundness inspection," *Int. J. Prod. Res*, vol. 26, pp. 1921-1935, Dec. 1988.

[8] C. Shen, L. Wang, and Q. Li, "Optimization of injection molding process parameters using combination of artificial neural network and genetic algorithm method," *J. Mater. Process. Technol*, vol. 183, pp. 412-418, March 2007.

[9] B. Ozcelik and T. Erzurumlu, "Comparison of the warpage optimisation in the plastic injection moulding using ANOVA, neural network model, and genetic algorithm," *J. Mater. Process. Technol*, vol. 171, pp. 437-445, Feb. 2006.

[10] S. S. Aminabadi, P. Tabatabai, A. Steiner,... G. Berger-Weber, "Industry 4.0 In-Line AI Quality Control of Plastic Injection Molded Parts," *Polymers Basel*, vol. 14, pp. 3551, Aug. 2022.

[11] H. Gao, Y. Zhang, X. Zhou, and D. Li, "Intelligent methods for the process parameter determination of plastic injection molding," *Front. Mech. Eng*, vol. 13, pp. 85-95, March 2018.

[12] A. Yuan, A. Coenen, E. Reif, and D. Ippolito, "Wordcraft: Story Writing With Large Language Models," in *27th International Conference on Intelligent User Interfaces*, 2022.

[13] J. Wei, M. Bosma, V. Y. Zhao,... Q. V. Le, "Fine-tuned Language Models Are Zero-Shot Learners," in *ICLR 2022 - 10th Int. Conf. Learn. Represent*, 2022, pp. 1-46.

[14] L. Wu, Z. Zheng, Z. Qiu,... E. Chen, "A Survey on Large Language Models for Recommendation," *World Wide Web*, vol. 27, no. 5, p. 60,2023.

[15] T. B. Brown, B. Mann, N. Ryder,... D. Amodei, "Language Models are Few-Shot Learners," *Adv. Neural Inf. Process. Syst*, vol. 30, pp. 1877-1901, May 2020.

[16] Z. Zhang, A. Zhang, M. Li, and A. Smola, "Automatic Chain of Thought Prompting in Large Language Models," in *11th Int. Conf. Learn. Represent. ICLR 2023*, 2023.

[17] J. Kaplan, S. McCandlish, T. Henighan,... D. Amodei, "Scaling laws for neural language models", arXiv.org, 2020. [Online]. Available: https://arxiv.org/abs/2001.08361 *Scaling Laws for Neural Language Models*, 2020.

[18] X. Wang, J. Wei, D. Schuurmans,... D. Zhou, "Self-Consistency Improves Chain of Thought Reasoning in Language Models," 11th Int," *Conf. Learn. Represent. ICLR*, pp. 1-24, 2023.

[19] A.B. and Arcas, "Do Large Language Models Understand Us?" *Daedalus,* vol. 151, pp. 183-197, May 2022.

[20] A. Abid, M. Farooqi and J. Zou, "Large language models associate Muslims with violence," *Nat. Mach. Intell,* vol. 3, pp. 461-463, June 2021.

[21] M. Shanahan, "Talking about Large Language Models," *Commun. ACM,* vol. 67, pp. 68-79, Feb. 2024.

[22] W.-T. Huang, Z.-Y. Tasi, W.-H. Ho, and J.-H. Chou, "Integrating Taguchi Method and Gray Relational Analysis for Auto Locks by Using Multiobjective Design in Computer-Aided Engineering," *Polymers Basel,* vol. 14, pp. 644, Feb. 2022.