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Original Article

SQ-3DP: A Novel Dataset for Predicting Surface Quality in 3D Printing using Machine Learning

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Abstract - *Optimizing ambient factors and machine operating parameters in 3D printing remains challenging due to the lack of real-time datasets for Machine Learning (ML). To address this, this research introduces the novel SQ-3DP dataset, aimed at predicting product surface quality using ML techniques. The dataset includes machine operating parameters such as nozzle temperature, bed temperature, and nozzle speed, alongside environmental factors like room temperature, humidity, and vibration. Experiments are conducted at three nozzle speeds (30, 50, 70 mm/sec) to analyze the impact of these factors on surface quality. Ambient parameters are collected using sensors and stored on an Arduino, with PCA and scaling applied for preprocessing. Exploratory and correlation studies validated the dataset's suitability, with PCA preserving critical variance. The SQ-3DP dataset shows significant promise for ML-driven advancements in 3D printing, with models such as KNN, SVM, and Naive Bayes achieving high performance, particularly SVM, for accurate surface quality prediction.*

Keywords *- Additive manufacturing, 3D printing, Machine Learning, Surface quality, SQ-3DP dataset, PCA.*

1. Introduction

The concept of 3D printing has become a transformative force in the manufacturing sector by producing unmatchable flexibility and precision in fabricating the parts for various applications [1, 2]. This ground-breaking technique is now used for rapid fabrications of customized components, pushing innovations in industries such as automobile, aerospace and biomedical fields. It plays a significant role in the production of medical equipment, such as prosthetics and orthopaedic implants [3]. Despite all these advantages, challenges persist due to inconsistencies in material properties, environmental conditions, and printer calibrations [4].

Further to address the limitations, Artificial Intelligence (AI) and ML are being extensively used to drive the innovation in Additive Manufacturing (AM), particularly in 3D printing systems [5, 6].

The proposed technology aims to enhance efficiency by considering real-time environmental parameters, such as temperature, humidity, and vibrations, in the printing process. However, the lack of ample datasets continues to impede the seamless integration of ML in real-time applications [7].

ML employs statistical methods to identify trends and forecast outcomes in various multimodal datasets [8]. Predictive modelling is a key function of 3D printing, which aids in the optimisation of crucial factors, including print speed, temperature, and material utilisation [9]. This leads to increased manufacturing efficiency, quality, dependability, and print accuracy [10].

Additionally, feedback loops driven by AI and ML may make design recommendations and help select the best materials, which will accelerate innovation and the implementation of 3D printing in various industries [11]. Through real-time adjustments to factors like print speed and material composition, ML also tackles important issues associated with environmental unpredictability, lowering errors and enhancing output quality [12].

The machine availability and downtime can be predicted greatly through the adoption of through the analysis of sensor data, machine learning [13]. ML-driven defect identification helps indicate the precise specifications of the printed components, which greatly improves the product quality [14]. This type of development demonstrates the application of ML concepts in the AM environment by enhancing scalability and operational efficiency.

Despite these successes, the majority of current research tends to ignore the influence of dynamic environmental factors and mostly uses static, machine-centric datasets. Studies that integrate real-time environmental data, such as temperature, vibration, and humidity, into prediction models for evaluating surface quality in Fused Deposition Modelling (FDM) are notably lacking. This disparity underscores the need for sensor-integrated datasets that capture the nuances of actual print environments.

For example, Goh et al. [4] and Ciccone et al. [10] study AI-based process optimisation without taking environmental effects into consideration, whereas Liu et al. [14] and Jiang et al. [15] concentrate on optimising process parameters and defect detection using machine log data. Peter et al. [16] provided insights into process forecasting by evaluating machine learning models, such as gradient boosting regression and polynomial regression, to predict Overall Equipment Effectiveness (OEE) in batch production. Additionally, [17, 18] demonstrated that ML can enhance industrial efficiency by forecasting OEE changes with 99.9% accuracy using Decision Tree algorithms, as evaluated with actual manufacturing data.

Okpala et al. [18] highlighted the importance of TPM in increasing OEE in the pharmaceutical sector, demonstrating that quality is the most significant aspect. In contrast, Sahoo et al. [19] focused on real-time predictive maintenance as an approach to addressing the inefficiencies of conventional maintenance in the semiconductor sector.

A major factor in sustaining highly capital-intensive industrial facilities is e-maintenance, which combines ICT with proactive tactics like e-diagnostics and e-prognostics [20]. Faria et al. [20] demonstrated how TPM, when examined using Minitab 21 and Design Expert 13, significantly enhanced vegetable oil production performance by focusing on quality, availability, and performance standards.

Qin et al. [21] identified the significant potential in the applications of ML concepts in the AM process control and defect identification. Conev et al. [22] adopted gradient boosting models to reduce the pre-print with an intuitive user interface, enabling comparison of CAD drawings with 3D printed components. Ale et al. [23] adapted Response Surface Methodology (RSM) to optimise OEE by concentrating on quality metrics. Anish et al. [24] investigated machine learning regressors to forecast tensile strength, surface roughness, and elongation, observing that additive and radial basis regressors were efficient in their respective fields.

Lukas Pelzer et al. [25] made another noteworthy attempt to overcome nonlinear process interdependencies by using Invertible Neural Networks (INNs) to calculate FDM settings automatically. With a prediction accuracy of up to 99.96%, their model, which was trained on combined process parameters and output quality, improved decision-making and decreased the need for expert input. For parameter optimisation in 3D printing, Dabbagh et al. [26] presented a unique GUI-integrated ML model; nonetheless, issues like data scarcity and processing costs continue to be obstacles.

Developing and evaluating a sensor-integrated, real-time dataset to enhance surface quality prediction in FDM 3D printing represents a novel approach that addresses the highlighted research gaps. The main contribution is the development of the SQ-3DP dataset, which integrates real-time environmental data like temperature, humidity, and vibration recorded by sensors and recorded using Arduino, with machine operating parameters, including bed and nozzle temperatures, in a novel way. To ensure that this combined dataset was appropriate for machine learning applications, it was meticulously cleaned and pre-processed.

Classification methods such as K-Nearest Neighbours (KNN), Support Vector Machines (SVM), and Naïve Bayes were used to assess its prediction performance. SVM emerged among these as the most precise and predictable model for forecasting and enhancing surface quality in components that are 3D printed. This research is novel because it incorporates real-time environmental variability into the predictive modelling process, departing from traditional, static datasets. This approach improves the practical application of machine learning in additive manufacturing and addresses important real-world problems.

A variety of operating settings were captured by the dataset, which was compiled employing three distinct print speeds: 30 mm/s, 50 mm/s, and 70 mm/s. To comprehend feature distributions, identify outliers, and investigate inter-variable connections, exploratory data analysis was carried out. PCA and feature scaling were two preprocessing methods used to lower dimensionality and enhance data quality. An important step towards developing intelligent, adaptable, and highly precise additive manufacturing systems is the application of machine learning algorithms to this modified dataset.

2. Materials and Methods

To investigate the influence of environmental conditions and machine operating parameters, such as nozzle temperature, bed temperature, and print speed, on surface quality in AM, this study integrates multiple sensors into an FDM 3D printer. The goal is to generate a comprehensive dataset that can be used to train AI models for predictive analysis. The setup incorporates key sensors, including the DHT11 temperature and humidity sensor, NTC Thermistor 100k for nozzle temperature monitoring, a dedicated humidity sensor, and the SW-420 vibration sensor. These sensors continuously collect real-time data during the printing process, enabling a dynamic understanding of how various parameters affect the final print quality. As illustrated in Figure 1, the sensor-integrated 3D printer forms the basis for the generation of the SQ-3DP dataset. This dataset is subsequently used to evaluate the printer's performance. Finally, the surface quality of the printed objects is assessed using standardized measurement techniques to ensure that the final products meet high precision and quality standards.

The experiments were conducted using the Ender 3 V2, a versatile and widely adopted FDM 3D printer known for its reliability and precision. The printer offers a build volume of 220 × 220 × 250 mm and has overall dimensions of 475 × 470 × 620 mm, with a total weight of approximately 7.8 kg. It supports a layer resolution range of 0.1–0.4 mm and a maximum printing speed of up to 180 mm/s. The standard nozzle diameter is 0.4 mm (interchangeable), and it accommodates a 1.75 mm filament diameter. The printer is capable of reaching a maximum nozzle temperature of 255°C and a bed temperature of up to 100°C, making it compatible with commonly used thermoplastics such as PLA and ABS.

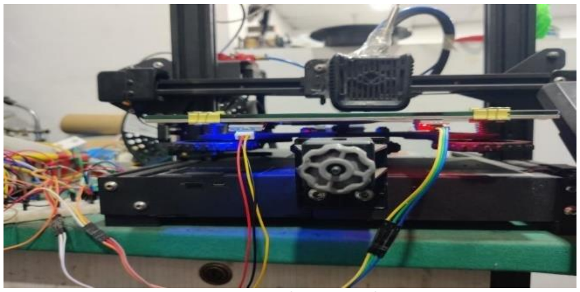

Fig. 1 Integration of sensors for 3D printers

For the purpose of this study, PLA filament was used under consistent operating conditions. Figure 1 depicts the detailed information about the sensor integration. The printing parameters were set as follows: layer height of 0.3 mm, wall thickness of 1.2 mm, infill density of 20% with a line pattern, nozzle temperature maintained at 205°C, and bed temperature set at 50°C. To assess the impact of print speed on surface quality, three different material deposition speeds, 30 mm/s, 50 mm/s, and 70 mm/s, were employed. These settings were chosen to simulate typical FDM printing scenarios and introduce controlled variations in surface finish outcomes.

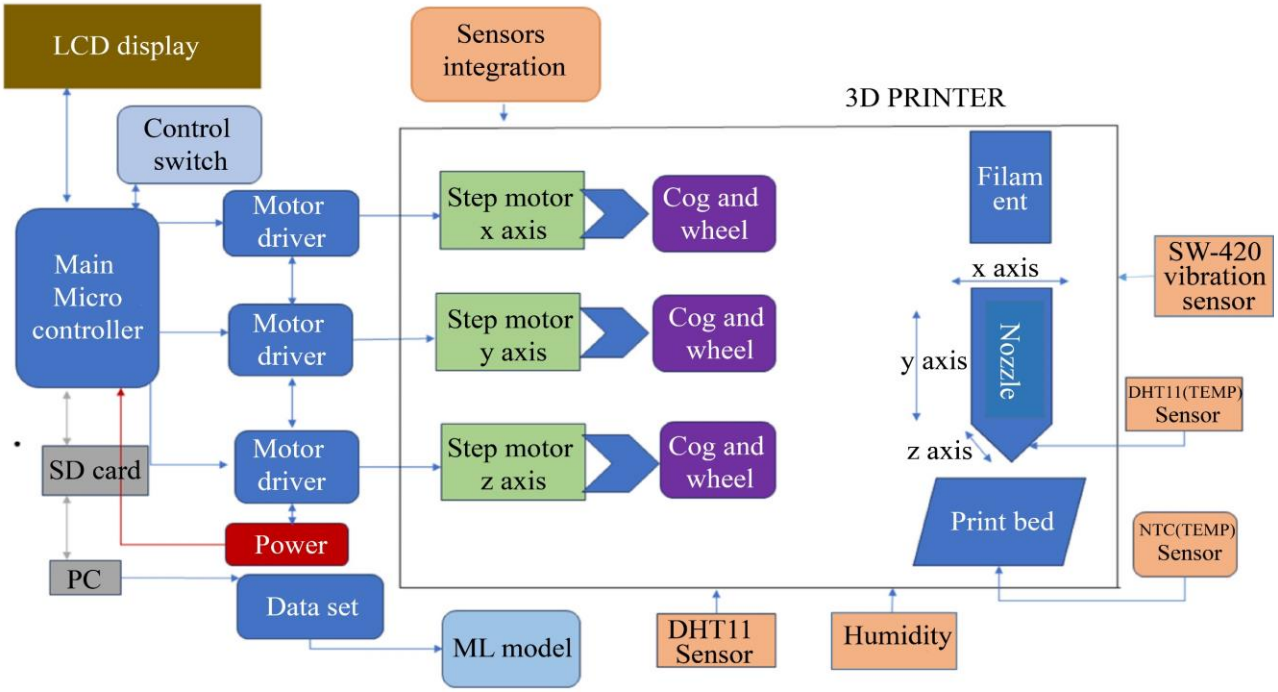

Fig. 2 Proposed framework for the generation of the SQ-3DP dataset

2.1. Sensor Integration and Roles

To collect environmental and process data, four types of sensors were integrated with the printer. The details of the sensors are shown in Table 1.

- DHT11 was used to monitor ambient and bed temperature as well as humidity.
- NTC Thermistor 100k measured the real-time nozzle temperature to prevent overheating.
- A dedicated humidity sensor monitored environmental moisture levels, which can adversely affect hygroscopic filaments like PLA.
- SW-420 vibration sensor captured mechanical disturbances that could impact layer adhesion and surface smoothness.

Table 1. Details of the sensors used to capture the data

Sensor	Principle	Measurement range	Least count
DHT11 Temperature	Polymer film's electrical response.	0 to 50 °C	0.1 °C
NTC thermistor 100k	Sintered semiconductor temperature sensing	-40 to 150 °C	0.1 °C
Humidity	Air thermal conductivity sensing	10 to 90 %	1 %
SW-420 vibration sensors	Vibration detection via a switch	0 to 420 mm/s	0.01 mm/s

Figure 2 shows the hardware integration setup. The dataset required for training machine learning models to predict surface quality was collected from all integrated sensors during the printing process at various nozzle speeds. These sensors were interfaced with an Arduino microcontroller, which served as the central data acquisition unit. Real-time data comprising environmental and machine parameters was recorded continuously and stored on an SD card connected to the Arduino. This setup allowed efficient logging of high-volume data for subsequent analysis.

2.2. Surface Quality Measurement

To accurately label the surface quality of the printed parts, physical measurement techniques were employed. Specifically, surface texture was evaluated using the Rubert surface roughness comparator (as shown in Figure 3), which enables a tactile and visual comparison against standardized roughness samples. Based on the surface roughness (Ra) values, printed samples were categorized into three classes as outlined in Table 2.

Table 2. Surface roughness categorization

Surface Roughness (μm)	Categorization
3.2 to 6.3	Good
6.3 to 12.5	Moderate
Greater than 12.5	Bad

This categorization was used to define the target labels for machine learning classification tasks. It ensured that the models were trained with data grounded in real-world physical measurements, thereby enhancing prediction accuracy and reliability.

Following data collection and labelling, the SQ-3DP dataset was structured to include seven features: bed temperature, nozzle temperature, room temperature, humidity, vibration, nozzle speed, and surface quality.

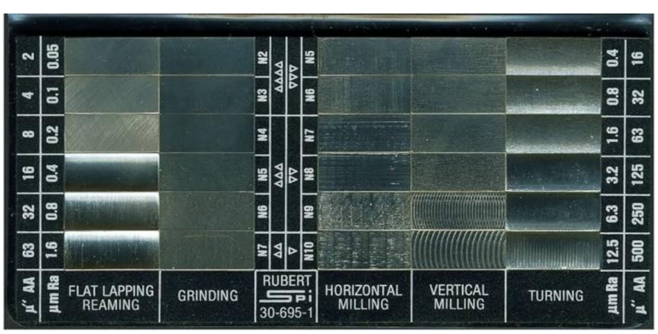

Fig. 3 Rubert surface roughness comparator

The first six features were derived from the sensors and printer settings, while the surface quality column served as the categorical target variable with three distinct classes: *Good*, *Moderate*, and *Bad*. The final dataset consisted of 12,177 samples, with the distribution of these categories presented in Figure 4. This comprehensive dataset provides a solid foundation for developing machine learning models capable of predicting surface finish based on real-time sensor and process data.

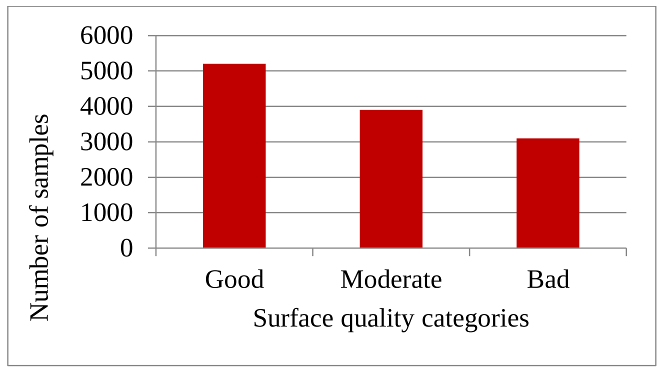

Fig. 4 Distribution of the dataset based on surface quality

These sensors were connected to an Arduino Mega 2560 microcontroller, with data logged every second via an SD card. Calibration of all sensors was performed prior to deployment using laboratory-grade equipment and standardized methods (e.g., saturated salt solutions for humidity calibration, vibration calibrators for SW-420). This ensured reliable, time-synchronized data collection.

2.3. Data Preprocessing and Rationale for PCA

To ensure high model performance, a structured preprocessing pipeline was implemented. The steps and their justifications are as follows:

2.3.1. Normalization

All numerical features were scaled to a 0–1 range using Min-Max normalization. This step is crucial, particularly for algorithms like KNN and SVM, to avoid features with higher magnitudes (e.g., vibration amplitude) from dominating model learning.

2.3.2. Handling Missing Values:

Sporadic sensor dropouts were observed (mostly in vibration readings). These were corrected using forward-fill interpolation, which preserves time continuity without artificially inflating variance.

2.4. Principal Component Analysis (PCA)

PCA was employed for dimensionality reduction, retaining at least 95% of the variance. This was motivated by several reasons:

- To remove multicollinearity, especially between nozzle and bed temperatures, and between humidity and room temperature, which showed a strong inverse correlation of -0.96.
- To enhance generalization by reducing overfitting caused by redundant features.
- To improve computational efficiency, particularly in model training and cross-validation stages.

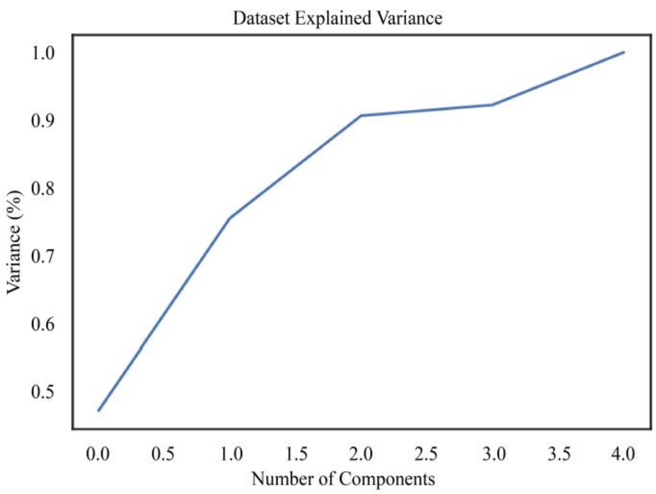

Fig. 5 PCA Plot

PCA transformed the correlated input space into a new orthogonal space of principal components, each explaining a significant portion of the dataset's variance. This allowed the dataset to retain its informational richness while being simpler to model. As demonstrated in the PCA plot (Figure 5), reducing from six to four components retained over 95% of the variance.

3. Machine Learning

Three supervised machine learning algorithms, K-Nearest Neighbours, Support Vector Machines, and Naïve Bayes, were trained and assessed using the SQ-3DP dataset in order to forecast and optimise surface quality in FDM-based additive manufacturing. The efficacy of each model in dividing surface quality into "Good," "Moderate," and "Bad" categories was evaluated using accuracy, precision, recall, and F1-score.

3.1. K-Nearest Neighbours (KNN)

A popular non-parametric and user-friendly machine learning technique for classification and regression applications is KNN. It classifies an input according to the majority label of its "k" nearest neighbours in the feature space, using the proximity principle. Given its robustness in handling complex, non-linear data distributions, KNN has proven suitable for applications in 3D printing, such as pattern recognition and defect classification.

In this study, a cross-validated accuracy plot (Figure 6) was of K. The x-axis represents different values of K, while the y-axis, used to evaluate model performance across various values, indicates accuracy, ranging from 99.72% to 99.90%. The plot demonstrates a general improvement in accuracy with higher K values, highlighting that a larger neighbourhood reduces noise sensitivity. However, excessive values of K can over-smooth the decision boundary, potentially reducing model precision.

The testing results for KNN are illustrated in Figure 7, showing high values for accuracy, precision, and recall, demonstrating KNN's capability to effectively generalize on unseen surface quality data.

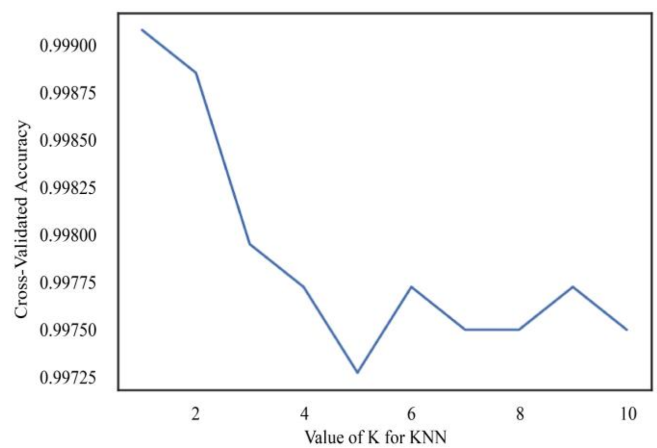

Fig. 6 Cross validated accuracy of a KNN classifier

3.2. Support Vector Machine (SVM)

SVM is a powerful classification algorithm that identifies the optimal hyperplane for separating classes in high dimensional space. It is particularly effective for nonlinear classification when combined with kernel functions such as the Radial Basis Function (RBF).

Model tuning was performed using hyperparameters C and gamma, with cross-validated accuracy plotted in Figure 8. The model achieved a peak accuracy of 99.89%, indicating its superior classification capabilities for this dataset. SVM's high performance stems from its ability to manage high-dimensional, multivariate inputs effectively, especially when features are correlated or overlapping.

Figure 9 shows the testing results of the optimized SVM model, highlighting excellent precision (99.86%), recall (99.90%), and F1-score (99.88%), making it the most effective classifier among the models evaluated.

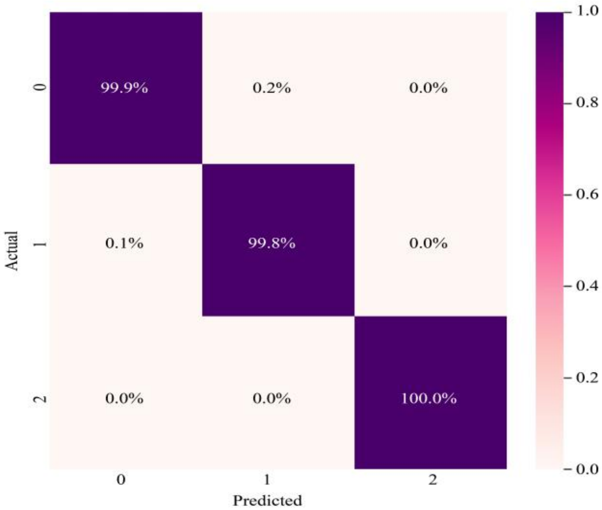

Fig. 7 Testing results for KNN

3.3. Naïve Bayes

As shown in Figure 10, the testing results for Naïve Bayes reflect solid but relatively lower performance compared to KNN and SVM, with an accuracy of 95.63%, precision of 94.40%, and recall of 97.03%. Its performance, though commendable, suggests that it is less suited for datasets with complex dependencies such as SQ-3DP.

Table 3. Model Performance

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
KNN	99.61	99.64	99.53	99.59
SVM	99.89	99.86	99.90	99.88
Naïve Bayes	95.63	94.40	97.03	95.54

3.4. Comparative Analysis

A summary of all model performances is presented in

From this comparative analysis, SVM emerged as the most accurate and balanced model, followed closely by KNN. Naïve Bayes, while efficient, lagged in performance due to its assumption of feature independence in a correlated sensor-based dataset.

3.4.1. Exploratory Data Analysis

Additional exploratory data analysis provided valuable insights:

- *Pair Plots (Figure 11):* Highlighted separable patterns between surface quality classes and revealed no significant outliers.
- *Correlation Heatmap (Figure 12):* Demonstrated strong relationships, such as a positive correlation (0.94) between nozzle and bed temperatures and a negative correlation (-0.96) between humidity and room temperature. These interactions validate the need for models that integrate both machine and environmental data for accurate predictions.

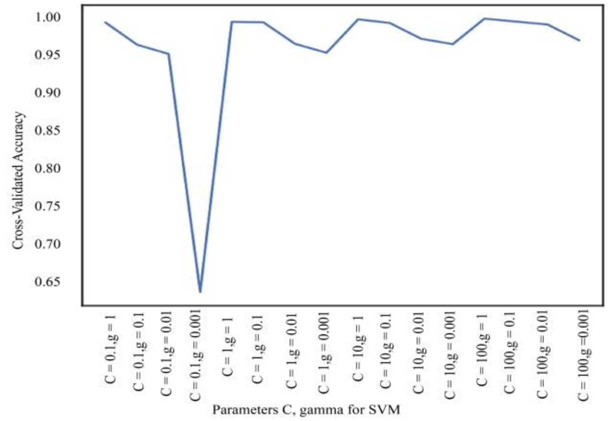

Fig. 8 Parameters C, gamma for SVM

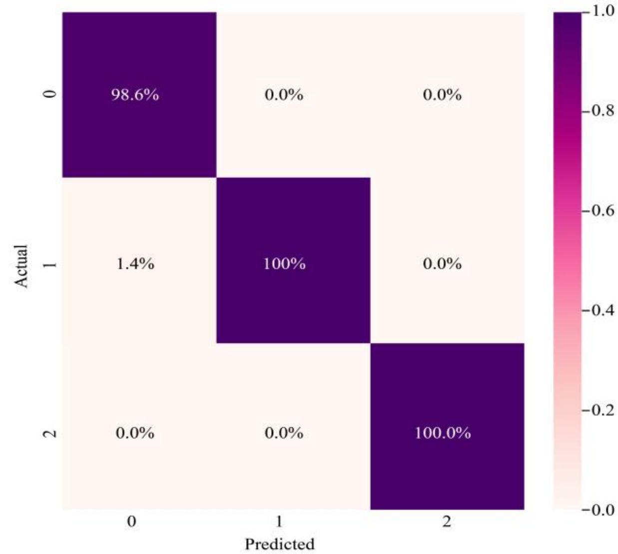

Fig. 9 Parameters C, gamma for SVM Vs cross-validated accuracy for the mean test score

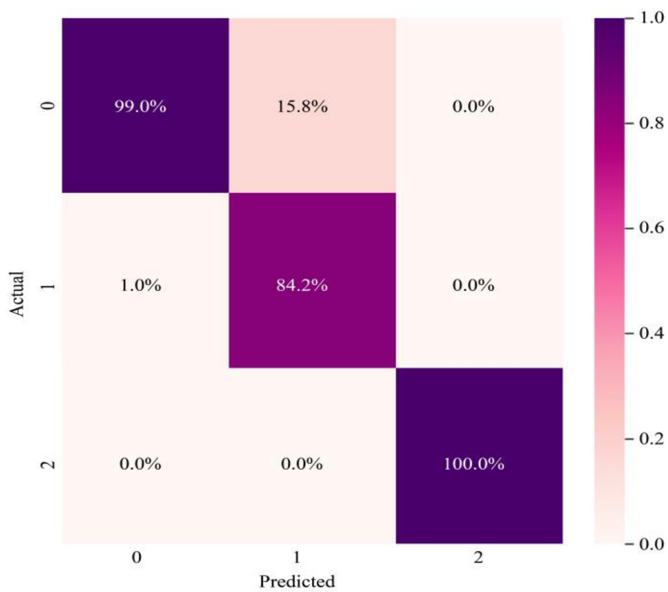

Fig. 10 Testing results for Naïve Bayes

3.5. Limitations

While the results are promising, several limitations of this study are acknowledged:

- *Limited Generalizability:* The dataset is specific to one printer model (Ender 3 V2) and one filament type (PLA). Applying the models to different printers or materials may require retraining or transfer learning.
- *Sensor Calibration Drift:* Over time, sensor accuracy can drift, which may affect data reliability unless recalibrated frequently.
  Model Scope: Only three classification algorithms were tested. More sophisticated models such as Random Forest, XGBoost, or neural networks could offer improved performance.
- *Surface Quality Validation:* Surface classification relied on visual assessment via a comparator.
- Advanced techniques like profilometry or 3D scanning could enhance objectivity.
- *Controlled Environment:* The experiments were conducted in a lab. Industrial conditions with fluctuating temperatures, dust, and machine vibrations may influence results differently.

4. Future Research Directions and Real-World Applications

The development of the SQ-3DP dataset lays the groundwork for a wide range of future research opportunities and practical implementations across multiple industries. Its integration of machine and environmental parameters in a real-time sensor-rich environment presents unique avenues for expanding the scope and impact of Additive Manufacturing (AM).

4.1. Advanced Machine Learning and AI Integration

To further improve the accuracy and robustness of surface quality prediction, future studies can explore the deployment of advanced machine learning models. Deep learning architectures such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory Networks (LSTMs) are particularly suited to learning spatial and temporal patterns from sensor data, allowing for finer-grained prediction and anomaly detection.

Additionally, online learning and reinforcement learning approaches can be introduced to facilitate real-time feedback and defect correction during the printing process. This would transform the static quality prediction model into a dynamic, adaptive system that optimizes print parameters on the fly.

4.1.1. Sensor Ecosystem Expansion

The inclusion of acoustic, thermal, optical, or laser-based sensors could further enrich the dataset, enabling a more comprehensive view of print quality and environmental influences. These sensors can capture subtle defects such as delamination, porosity, or thermal inconsistencies that traditional sensors may miss.

4.1.2. Cross-Material and Cross-Platform Generalization

The current study is limited to PLA filament and a single printer model. Future work can extend the dataset to include diverse materials such as ABS, PETG, or composites, as well as different printer architectures. Transfer learning methods could be applied to adapt models trained on one material or setup to others, improving the generalizability of AI models in AM.

4.2. Explainable and Trustworthy AI

With increasing deployment in regulated industries such as aerospace and biomedical manufacturing, the need for explainable AI (XAI) becomes critical. Tools such as SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) can help interpret predictions, build trust, and support certification and regulatory approval processes.

4.3. Integration with Digital Twin and Industry 4.0 Frameworks

The SQ-3DP dataset can be embedded into digital twin architectures to create real-time virtual replicas of the 3D printing environment. This would enable predictive maintenance, process simulation, and self-optimizing control, advancing the vision of smart factories under the Industry 4.0 paradigm.

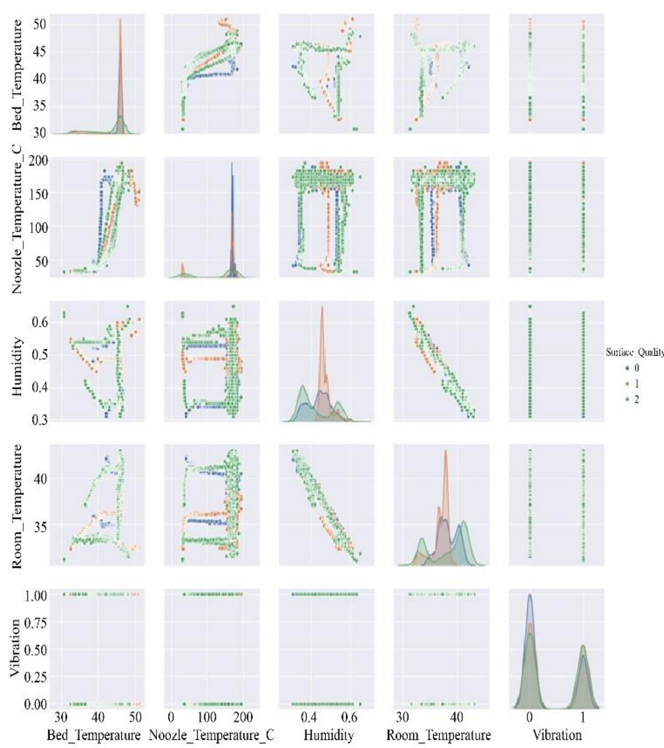

Fig. 11 Pair-Plot visualization of SQ-3DP dataset (0-Good,1-Medium,2-Bad)

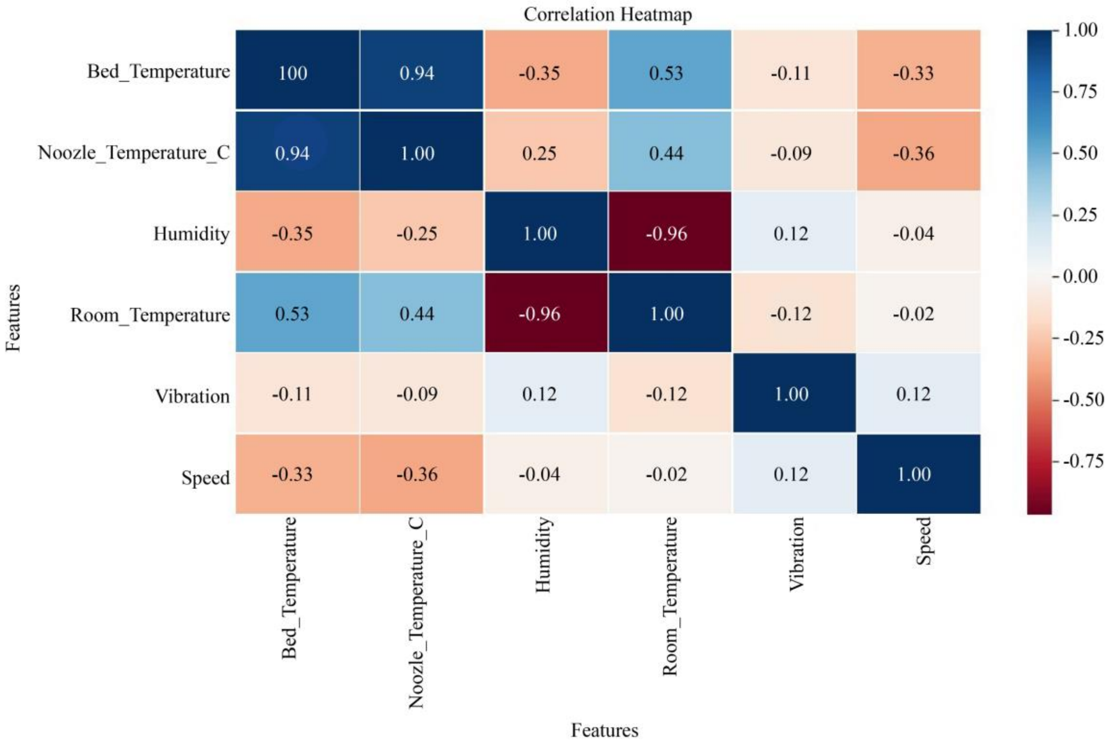

Fig. 12 Correlation visualization of the SQ-3DP dataset using a heatmap

4.4. Real-World Industrial Applications

The practical potential of this research spans several high-impact domains:

- In biomedical manufacturing, AI models trained on the SQ-3DP dataset can identify micro-defects in 3D-printed implants, enhancing safety and performance.
- In the aerospace industry, accurate surface prediction can ensure tight dimensional tolerances in mission-critical components like brackets and housings.
- In automated manufacturing environments, the dataset can power adaptive AM systems, enabling real-time quality assurance and reducing human intervention.

By combining these advanced approaches with real-world integration, the SQ-3DP framework can serve as a stepping stone toward fully autonomous, high-precision, and intelligent additive manufacturing ecosystems.

5. Conclusion

The study on the SQ-3DP dataset for Predicting Surface Quality in 3D Printing using Machine Learning is specifically focused on quantifying and optimize the FDM 3D printing process using Machine learning concepts. Compared to the other approaches, which primarily rely on the static machine parameters, the SQ-3DP dataset uniquely captures real-time data from both machine (nozzle temperature, bed temperature and printing speed) and environmental factors (room temperature, humidity and vibration), providing a holistic view of the process.

The Integration of a microcontroller (ARDUINO) system for obtaining live data from the sensors makes a significant enhancement over traditional datasets. This real-time dataset acquisition method allows capturing transient thermal and mechanical fluctuations, which are difficult to capture in traditional methods, making it a more dynamic dataset for modelling purposes.

Techniques such as Standard scaling and principal component analysis were adapted as preprocessing techniques for refining the dataset for ML. Four principal components extracted from six variables captured over 95% of the variance, ensuring that predictive performance remained the same. Adapting these steps improves the training speed and model interpretability when compared to earlier studies.

Further into the study, the correlation and empirical validations have shown the critical dependencies, such as the strong influence of printing speed on the surface finish, which was underrepresented in earlier studies, which was emphasizing on the thermal properties alone. The study, in combination with both thermal and mechanical factors, has provided a new insight to understand the effect of ambient conditions on the surface quality, an area seldom addressed with such depth in prior literature.

To analyse the effect of the dataset, three classifiers, viz. KNN, SVM and Naive Bayes were trained and evaluated. On the observations, SVM has achieved better accuracy compared to any other models previously published in outperforming across all the performance parameters, including accuracy, precision, recall and F1-score. The high-resolution sensor-enriched dataset, also with a panned preprocessing pipeline, is responsible for achieving better performance, which allowed for more reliable pattern detections and generalisation.

The SQ-3DP dataset represents a substantial advancement over state-of-the-art methods by offering real-time, multi-factorial data collection and demonstrating improved predictive accuracy through optimized machine learning workflows. This positions it as a critical enabler for intelligent, closed-loop control systems in additive manufacturing, fostering higher reliability, consistency, and surface quality in 3D printed parts.

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