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Use of Machine Learning to Improve Additive Manufacturing Processes

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Featured Application: Potential applications of the work include new artificial intelligence-based software for optimizing 3D printing and products and services realized through additive manufacturing.

Abstract: Rapidly developing artificial intelligence (AI) can help machines and devices to perceive, analyze, and even make inferences in a similar way to human reasoning. The aim of this article is to present applications of AI methods, including machine learning (ML), in the design and supervision of processes used in the field of additive manufacturing techniques. This approach will allow specific tasks to be solved as if they were performed by a human expert in the field. The application of AI in the development of additive manufacturing technologies makes it possible to be assisted by the knowledge of experienced operators in the design and supervision of processes acquired automatically. This reduces the risk of human error and simplifies and automates the production of products and parts. AI in 3D technology creates a wide range of possibilities for generating 3D objects and enables a machine equipped with a vision system, used in ML processes, to analyze data similar to human thought processes. Incremental printing using such a printer allows the production of objects of ever-increasing quality from several materials simultaneously. The process itself is also precise and fast. An accuracy of 97.56% means that the model is precise and makes very few errors. The 3D printing system with artificial intelligence allows the device to adapt to, for example, different material properties, as the printer examines the 3D-printed surface and automatically adjusts the printing. AI/ML-based solutions similar to ours, once learning sets are modified or extended, are easily adaptable to other technologies, materials, or multi-material 3D printing. They also allow the creation of dedicated, ML solutions that adapt to the specifics of a production line, including as self-learning solutions as production progresses.

Keywords: artificial intelligence (AI); machine learning (ML); additive manufacturing; 3D printing

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Citation: Rojek, I.; Kopowski, J.; Lewandowski, J.; Mikołajewski, D. Use of Machine Learning to Improve Additive Manufacturing Processes. *Appl. Sci.* **2024**, *14*, 6730. https://doi.org/10.3390/app14156730

Academic Editor: Rocco Furferi

Received: 1 July 2024
Revised: 29 July 2024
Accepted: 30 July 2024
Published: 1 August 2024

1. Introduction

Artificial intelligence (AI)and 3D printing are among the most important key technologies (followed by Internet of Things (IoT), Industrial Internet of Things (IIoT), blockchain, and 5G) that are changing the way people operate in the corporate, consumer, and professional world, and are major in healthcare/medicine, business, agriculture, education, and urban development [1]. Rapidly developing AI methods and techniques can creatively help machines and devices perceive, analyze, and even reason and predict in ways similar to human reasoning. The aim of this article is to present selected applications of AI methods, including machine learning (ML), in the design and supervision of processes used in the area of additive manufacturing (AM) techniques. This approach allows to solve specific tasks as if they were performed by a human expert in a given field. The use of AI in the development of AM technologies now makes it possible to support younger engineers with the knowledge of experienced experts in designing and supervising automatically implemented processes. This reduces the risk of human error and simplifies and automates the production of products and their parts, also as part of multi-material 3D printing. It can also have a positive impact on optimizing parameters or reducing the amount of waste. Additionally, ML, based on the data, extracts the rules that bind them, even if they are not obvious or have not been previously extracted and described. Artificial intelligence in 3D technology creates wide possibilities of generating 3D objects and enables a machine equipped with a vision system used in ML processes to analyze data similar to human thought processes. Additive printing using such a printer allows the production of objects of increasingly higher quality. The process itself is also precise and fast. The 3D printing system with artificial intelligence allows the device to adapt, for example, to various material properties, because the printer examines the 3D-printed surface and automatically adjusts the print. In addition, AI can help people cope with the abundance of information by extracting data that is useful in a specific case [2,3].

On the foundations of Industry 4.0, the Industry 5.0 paradigm is being created, in which design and manufacturing are human-centered, resilient, and sustainable. Industry 5.0 will translate into Society 5.0 with an integrated cyber-physical platform in which people play a significant role. Such a digital transformation will modify several social sectors: health care, disaster management, and innovative economic models that include nature, and therefore a reconstruction of industry and society towards further technological progress is required [2,4–6].

In intelligent production, it is crucial to maintain a high level of production utilization. For this purpose, the production line must always have enough materials and semi-finished products, but too many materials stored in the warehouse would increase the factory's operating costs. Moreover, the efficiency of different production lines, and therefore the rate of material consumption, may vary. IIoT-based supervisory control and data acquisition (SCADA) systems are becoming increasingly popular, and performance estimation is performed using AI. In this way, a Customer-to-Business (C2B) safety stock management model is built in a manufacturing company. In this model, inventory is managed by the supplier. This is particularly important in cases where the life cycle of materials and products is short and susceptible to market fluctuations. In addition to effectively reducing inventory levels, we gain increased competitiveness of the entire production and sales ecosystem through the digital transformation of production with the support of AI and IIoT [3,7–11].

AI is revolutionizing AM (3D printing) by improving various aspects of the process, from design through production to finishing and fixing prints as far as predicting and monitoring their life cycle assessment (LCA) [12,13]. This is summarized in Table 1, but it does not exhaust all the possibilities still being explored.

Table 1. Essential areas of AI impact on AM processes (own version based on [4–6,14–16]).

Area	Task	Description
Workflow and supply chain optimization	Production planning	AI can optimize production schedules by analyzing demand forecasts, machine availability, and material supply. This ensures efficient use of resources and timely delivery of printed parts.
	Inventory management	AI can predict material consumption and manage inventory levels to ensure that materials are available when needed without overstocking, which can be costly to store (lean management).

Table 1. *Cont.*

Area	Task	Description
Design optimization	Generative design	AI algorithms can create complex and optimized designs that are difficult or impossible to develop using traditional design methods. Multiple scenarios for solving a design problem are explored, and design alternatives are generated and then optimized for various criteria (cost, material consumption, weight, strength, and others).
	Topology optimization	AI can take into account performance requirements and optimize the layout of materials in a given design space. This ensures that a given material is only used where it is needed, resulting in lighter and stronger parts and a cost-effective design.
Process control and monitoring	Real-time process monitoring	AI algorithms can be used to monitor the AM process in real time using sensor and camera data. AI models analyze this data in real time to detect anomalies, predict failures, and ensure the desired quality of printed parts. AI systems can analyze the printing process in real time, adjusting printing parameters to ensure each layer is printed correctly. This includes adjusting temperature, speed, and material flow based on sensor feedback.
	Defect detection	Computer vision and ML techniques can automatically check printed parts for defects. To do this, AI can compare the image of each layer or final parts with a set of standards or previous prints (classified as correct) to identify defects (cracks, warping, incomplete joints, and more).
	Predictive maintenance	By analyzing historical data from the machines, AI can predict when a 3D printer component is likely to fail and schedule maintenance before this happens. This minimizes downtime and extends the life of the equipment.
Materials development	Material property prediction	AI models can predict the properties of new and upgraded materials based on their composition and processing parameters. This accelerates the development of new 3D printing materials that are optimized for specific AM applications.
	Process parameter optimization	AI algorithms can optimize the processing parameters of specific materials, such as temperature, laser power, and print speed, to achieve the desired material properties and performance. This also applies to multi-material or multi-step printing, where, for example, the surface preparation/finish in the previous step determines the speed and quality in the next processing step.
Post-processing optimization	Automated finishing	AI can be used to optimize finishing steps, such as removing support structures or polishing/fixing/coloring surfaces. Machine learning algorithms can determine the most efficient way to finish parts based on their geometry and material, including the cost-optimal and least environmentally damaging (e.g., thickness and number of layers when painting).
Customization	Mass customization	AI can enable mass personalization by automating the customization of designs to individual customer specifications. This is particularly useful in industries such as healthcare (e.g., customized rehabilitation aids, implants, pre-operative preparation for surgeons) and consumer product manufacturing (e.g., personalized footwear, T-shirts, or jewelry).

Implementing AI in AM typically requires the following actions:

- Collecting extensive data from sensors, machines, and production processes;
- Selection of the above-mentioned data and using them to train AI/ML models to recognize patterns, predict results, and optimize parameters;
- Integration of AI models with existing production systems and workflows;

- Continuously improve, monitor, and update AI models with new data to improve the accuracy and efficiency of the models themselves and entire processes [7–10,17,18].

2. Materials and Methods

2.1. Dataset

A dataset of 3D printers mass-printing scientific and industrial solutions (including prototypes) taken in 2023/2024 was analyzed. Data were read from the systems recorded and analyzed to full accuracy and have been rounded for presentation purposes only. We used data from printers using fused deposition modeling (FDM). Data sources were data taken from Slicer configuration files and results (time, material consumption, etc.) after slacking, as well as the software Prusa Slicer (Prusa Research, Prague, Czech Republic) and UltiMaker Cura (UltiMaker, Geldermalsen, The Netherlands).

Data were collected in an .xls spreadsheet (Microsoft Excel (2021), Microsoft, Redmond, WA, USA) and .csv spreadsheet for model learning purposes.

Of the 297 parameters measured, 280 underwent selection for confidence, completeness, and removal of outliers. Seventeen parameters did not meet the requirements. Over the course of the study, the number of input parameters was reduced to 81 (highlighted in red and yellow in the Supplementary Data File). The Supplementary File contains the input parameters: (parameters used in the Slicer (cutting/cutting software) for FDM) in the following layout: parameter name, description, example values, and an explanation of the colors used (red, yellow, white).

The data included 590 records. A set of 413 (70% of 590) was used for training. Each consists of input and output data. The content of the input data was adapted for efficiency and included 60 selected print parameters. Four optimal outputs were predicted for each input dataset:

- Bed temperature [degrees Celsius];
- Cooling [fan speed in rev/minute];
- Layer speed [m/s];
- Layer width [mm].

As our aim was to optimize the aforementioned output parameters, we selected these output parameters among eight other potential output parameters as the best factors/predictors of good quality prints after preliminary tests.

Each of the above categories is assigned a numerical value. The range of input and output variables in the ANN model is, for each of the above values, normalized to a range of 0–1 separately for each input or output.

As far as possible, the data were checked for balance and balanced so that they did not cover the outliers alone or the midpoints alone.

It should be noted that in the study our model was learned on specific industry data, which may weaken its ability to generalize to a more diverse dataset, and this will require future modification and possibly adaptation to a different, new dataset. In analyzing complex industry data, we relied on the authors' knowledge and previous experience. We measured and predicted values with original accuracy, i.e., FDM printing accuracy:

- Dimensional accuracy: ± 0.1 mm to ± 0.3 mm;
- Layer thickness: 0.05 mm to 0.4 mm (depending on printer and settings);
- Positional accuracy: ± 0.05 mm to ± 0.1 mm (depending on printer).

2.2. Methods

This study used a data-driven approach, i.e., machine learning: a semi-automated solution based on pre-prepared scripts (ML.NET in Visual Studio 2022, Microsoft, Redmond, MA, USA). The primary criteria for evaluating the effectiveness of the solutions were RMSE value and accuracy (separately for learning and testing). It is a semi-automatic solution based on previously prepared scripts. It relies on the use of pre-existing scripts or code templates to develop an AI solution. These scripts often contain predefined algorithms, configurations, and processing steps. Developers can combine and customize scripts for a specific use case. This ensures faster implementation compared to building the solution from scratch. This may be an appropriate solution for simpler tasks that do not require highly specialized models. The level of customization and flexibility may be limited by the scripts available, and updates and modifications may be simpler but may still require an understanding of the underlying code. The proposed approach may be useful for rapid prototyping or when time and resources are limited—as in the case of 3D printers and data derived from them. The main features of the proposed semi-automated solution are as follows:

- Moderate customization: relies on existing scripts, potentially limiting customization options;
- Accuracy and complexity: may be less accurate, but it has simpler ones suitable for simpler tasks;
- Software development effort: can be implemented faster, but it may not have the same degree of optimization (Figures 1–3).

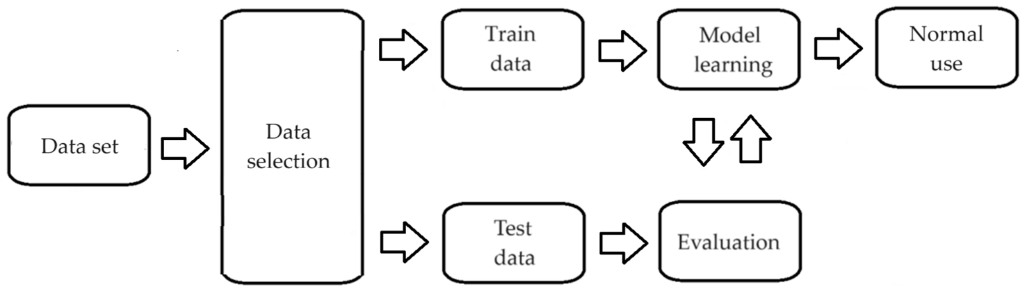

Figure 1. General concept of ML model (own version).

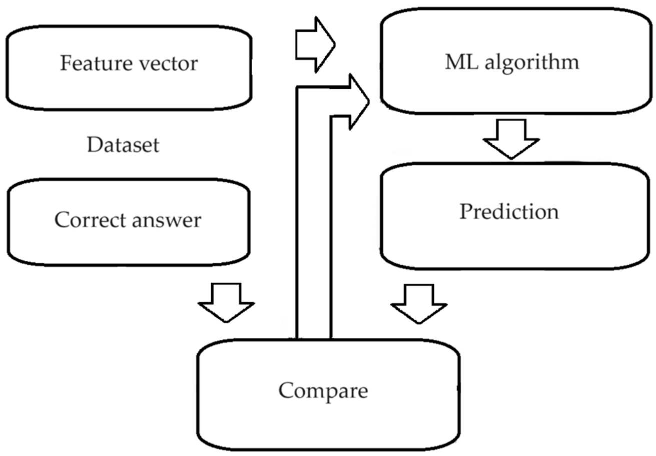

Figure 2. ML training process (own version).

Figure 3. The ML-based model used to make predictions from the feature vector (own version).

The estimated learning time (local CPU, AMD Ryzen 5 5600U 64-bit CPU, Radeon 2.30 GHz GPU, and 16 GB RAM) did not exceed 10 min in any case. This confirms that this type of data can be analyzed locally or in the cloud. The advantage of the ML.NET environment is the simultaneous checking of many algorithms (even over 100) and the identification of the best one, as well as a relatively short configuration (for a person who has a previously prepared environment and project, e.g., catalogs with individual data in the case of classification) which takes about 20 min. In the case of the traditional approach, it takes much longer and must be performed separately for each network configuration, but it allows the selection of solutions adapted to the form of the data. This is because some of the knowledge comes from the designer's experience rather than being encoded in the system, which makes manual network tuning unique and difficult to reproduce in an automated system. The automatic approach is faster, but it is unknown whether the speed advantage is enough to achieve better model performance. In this case, a dedicated AI solution simply allows for better personalization of the offer, e.g., towards reducing costs or increasing the efficiency of the PV network at specific times of the day. On the other hand, the AI algorithm allows you to capture more dependencies within processes and user behavior that are not obvious and noticeable to humans, and then include them in the control algorithm. Therefore, the choice of a specific solution may depend on user preferences. The results were exported to .xlsx and .csv files, and in the case of ML.NET, the C# code was also available in the form of two projects (ML.ConsoleApp and ML.Model in MS Visual Studio 2022 (Microsoft, Redmond, WA, USA)) for furtherprocessing.

ML.NET is an open-source cross-platform machine learning framework developed by Microsoft. It is designed to enable .NET developers to easily integrate machine learning into .NET applications, leveraging a wide range of machine learning tasks. As a scientific tool, ML.NET offers several features and capabilities that make it suitable for data analysis and research purposes:

1. Comprehensive machine learning capabilities: Classification: supports binary and multi-class classification tasks;
    - Regression: enables predictive modeling for continuous variables;
    - Clustering: makes it easier to group similar data points together;
    - Anomaly detection: identifies unusual patterns that do not match expected behavior;
    - Recommendation systems: provides tools to create personalized recommendation systems;
    - Natural language processing (NLP): supports text classification, sentiment analysis, and other NLP tasks;
    - Image processing: includes image classification and object detection capabilities.
2. Integration with the .NET ecosystem:
    - Integrates with other .NET technologies, making it convenient for developers familiar with the .NET ecosystem;
    - Supports deployment across a variety of environments, including cloud, on-premises, and edge.
3. Automated Machine Learning (AutoML): offers AutoML capabilities to automate the process of model selection, hyperparameter tuning, and feature engineering, thereby simplifying the workflow for non-experts;
4. Data processing and transformation:
    - Provides a rich set of tools for loading, cleaning, and transforming data;
    - Supports various data sources including databases, files, and in-memory collections.
5. Interoperability with other tools: can be used in conjunction with popular data science tools and libraries such as TensorFlow, ONNX, and Infer.NET, allowing you to incorporate pre-trained models from other platforms;
6. Model training and evaluation: offers flexible APIs for training and evaluating custom models, and provides metrics and visualization tools to evaluate model performance;
7. Scalability and performance: it is performance-optimized and efficient in handling large datasets and scales to accommodate growing data volume and complexity.

Its ability to handle a variety of data types combined with integration with other scientific tools and frameworks makes it an attractive option for researchers and developers who want to leverage machine learning in their work.

3. Results

The task turned out to be difficult due to the modeling conditions. Achieving satisfactory results (the threshold was set at 85%) with a relatively small dataset required not only careful data preparation, but also many tests and model tuning, including the selection of input parameters.

A total of 2457 models were made, the number of models made for one parameter configuration was 46, and the average training time for one model was 95.64 s. The best algorithm to accomplish this task turned out to be FastForestOva, which achieved an accuracy of 97.56%. In selected single cases accuracy achieved 100%, but it can be overmatched. Detailed data are presented in Table 2.

Table 2. Five best algorithms in the study.

Algorithm	Microaccuracy [%]	Macroaccuracy [%]
FastForestOva	97.56	97.23
LbfgsLogisticRegressionOva	94.44	93.89
SdcaMaximumEntropyMulti	89.11	89.23
LightGbmMulti	87.34	87.12
FastTreeOva	85.12	84.87

FastForestOvais based on a random forest (an ensemble of decision trees), in which each tree generates a Gaussian distribution by prediction. To find the Gaussian distribution closest to the combined distribution for all trees in the model, aggregation is performed on the ensemble of trees. This provides better coverage and accuracy than single decision trees.

LbfgsLogisticRegressionOva is based on the Broyden–Fletcher–Goldfarb–Shanno method with limited memory (L-BFGS), which replaces the computation of the Hess matrix with Newton's method with a faster and cheaper approximation and fast convergence based on a limited number of historical states to compute the direction of the next step. This is most relevant for solving problems with multidimensional feature vectors. However, it should be noted that the use of a larger number of historical states can lead to better approximations. Moreover, a flexible regularization of the network is used here: a linear combination of L1-norm (LASSO) and L2-norm (ridge), which are complementary (e.g., using L1-norm can increase the correctness of the trained algorithm for sparse data, bringing some weights to zero), and L2-norm regularization is preferred for data that are not sparse (avoids using large weights).

SdcaMaximumEntropyMulti is based on a linear multi-class classifier model trained by coordinate descent with a loss function making the trained model a classifier with maximum entropy. It is an extension of the coordinate descent method towards a higher rate than L-BFGS and a truncated Newton's method for large and sparse datasets. In doing so, it uses empirical risk minimization (ERM) to optimally formulate the problem based on the collected data. However, such a model may be good at describing training data, but it may not predict the correct results as accurately for previously unknown data.

LightGbmMulti is based on the implementation of a gradient decision tree. It is efficient, providing faster training and higher performance, lower memory consumption, better accuracy, and support for large-scale parallel, distributed, and GPU learning.

FastTreeOva is based on an implementation of the Multiple Additive Regression Trees (MARTs) algorithm, i.e., gradient enhancement. The predictive model here is a set of weaker predictive models, as this algorithm builds regression trees (with scalar values in the leaves) sequentially and incrementally based on a predefined loss function to measure the error for each step and its correction in the next step. The optimal tree from the above set of trees is selected using an arbitrarily differentiable loss function.

The model achieved an accuracy of 97.56%, which means it correctly predicts or classifies 97.56% of the instances in the test dataset. This is a high level of accuracy, suggesting that the model is reliable and robust (Figure 4). The model is likely concerned with predicting certain outcomes related to 3D printing processes and classifying data points into predefined categories. These may include predicting print quality, identifying defects, classifying material types, or optimizing printing parameters. An accuracy of 97.56% means that the model is precise and makes very few errors. This is crucial in applications where precision is crucial, such as manufacturing or medical device manufacturing. A high accuracy rate suggests that you can trust the model to perform consistently, reducing the risk of failure or defects in the 3D printing process. With such high accuracy, the model can significantly increase the efficiency of the 3D printing process by minimizing trial and error, reducing material waste, and optimizing production time.

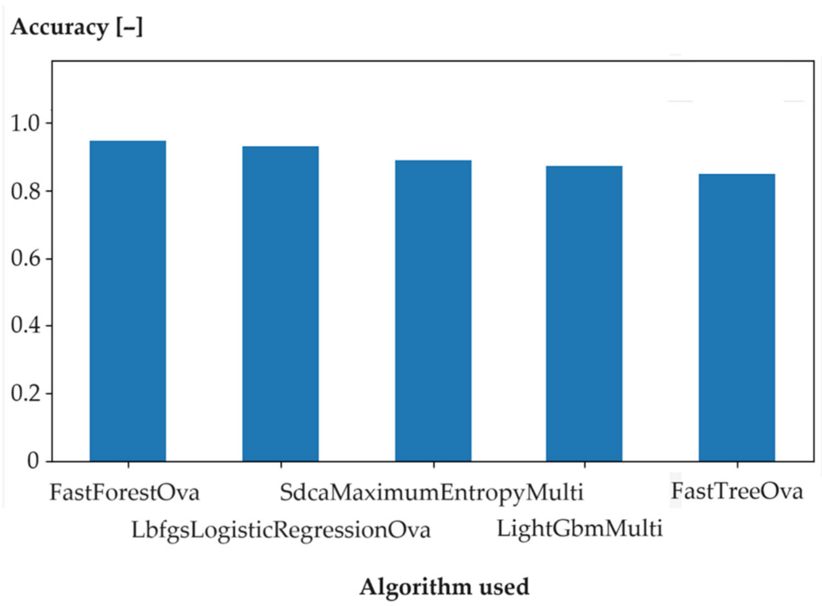

Figure 4. Comparison of models.

Achieving an accuracy of 97.56% in ML-based 3D printing prediction and classification represents a significant advance in the field. This high level of accuracy increases the reliability, efficiency, and applicability of 3D printing technology in a variety of industries. It paves the way for more precise and customized manufacturing processes, ultimately leading to innovation and increased productivity. The model's success demonstrates the potential of machine learning to revolutionize manufacturing and related fields.

A faster implementation of a similar computational task in the future would certainly be improved by a smaller data spread, a larger dataset, and better preparation for data auditing. Please note that the burden of responsibility for success is divided equally between two tasks: data preparation and algorithm selection. Data selection took the most time, because despite having computational tools, it had to be refined manually, also based on the team's knowledge and experience in the field of 3D printing, and not only AI. Modeling and selection of algorithms were mostly performed automatically and generated relatively high computational costs, but they did not involve a team of specialists as much. Therefore, the second part of the task is already automated (the program generates, among others, API), but more effort should be put into automating the acquisition and selection of 3D printing data, including bidirectional data (i.e., sending raw data from 3D printers to ML systems, and vice versa: optimal settings for printers). This will require standardization and better software integration. Please note that the main programming language supported by

Visual Studio 2022 is C#. This means that some applications working in Python, Java, or Kotlin will have to be rewritten.

4. Discussion

The results we show are in line with and an extension of global trends, previous studies, and of the working hypotheses. However, for a fuller understanding of them, these results and their implications should be discussed in the broadest possible context.

Smart production as an element of Industry 4.0 and Industry 5.0 is a key element of the production monitoring system via AI and IIoT, also in remote production management. Under the Internet of Everything (IoE), smart factories typically control IoT-based SCADA systems. This not only improves the utilization and timeliness of deliveries but also predicts them through AI based on product sales data at a lower level of the supply chain. You can effectively estimate consumption of key materials and proactively report demand to key material suppliers upstream in the supply chain so they can quickly ensure sufficient safety stocks that integrate the value chain [3].

The synergy between ML and AM has the potential to revolutionize the design and production of AM-printed components due to the improved efficiency of such solutions. Here, ML makes it possible to semi-automatically or automatically capture the relationships between the parameters of AM techniques quickly and accurately. However, this usually requires large and structured datasets. Investigated applications of ML in AM include design and process optimization, microstructure analysis, material selection, and quality control. Prospective applications of ML in AM include the use of advanced ML models and the development of new sensors and applications of ML in new AM-related fields, such as medical applications, covered by additional requirements [19]. The AI/ML-based revolution is a good alternative for solving many data analysis and decision-making problems, but it needs to be tested for each application, as it does not perform always and everywhere with the same efficiency [20], depending also on the form and selection of the data [21].

The advantages of using ML.NET in scientific and industrial research are as follows:

- Accessibility: makes ML accessible to .NET developers without requiring extensive data science expertise;
- Flexibility: provides a wide range of algorithms and tools that can be tailored to your specific research needs;
- Efficiency: streamlines your machine learning workflow, from data processing to model deployment;
- Community and support: powered by growing community, providing continuous updates and support [22–24].

The implications lie in the following:

- Less waste: thanks to correct prediction and classification, the model reduces material waste, which directly affects the cost;
- Fewer reworks: high accuracy minimizes the need for reprints, saving time and resources;
- Faster printing: thanks to accurate predictions and classifications, the entire production process becomes faster and more efficient;
- Scalability: the reliability of the model allows the production process to be scaled without loss of quality;
- Advanced research: models can drive research in materials science and manufacturing processes, providing insight into the 3D printing process;
- Potential new applications: high accuracy opens up new opportunities in fields such as aerospace, the automotive industry, and bioprinting, where precision is paramount [25,26].

The implications of achieving 97.56% accuracy in ML-based 3D printing prediction and classification extend beyond technical and engineering fields. For non-engineers, this high level of accuracy can have several practical and beneficial effects in a variety of fields.

Students and teachers can use 3D printing with confidence, knowing that the prints will be accurate. This enables more interactive and engaging learning experiences. The high accuracy of the model simplifies the 3D printing process, making it easier for non-engineers to learn and operate without extensive technical training. Educators can create precise and custom learning aids, models, and prototypes, improving students' learning experience. Educational institutions can more easily implement 3D printing technologies, making them accessible to a wider range of students. Precise predictions enable the creation of custom prostheses and orthoses tailored to the individual needs of patients, improving comfort and functionality. Doctors (including surgeons) can use accurate 3D-printed models for preoperative planning, leading to better outcomes. Medical professionals can quickly produce and test new devices and tools, accelerating innovation in patient care. Patients can be better informed about their conditions and treatments thanks to precise anatomical models. All 3D printing users can realize their creative ideas with fewer technical obstacles. For example, they can create personalized items such as custom phone cases, jewelry, or household items with high precision and reliability. High accuracy reduces the risk of failed prints, making it easier for non-engineers to take on complex projects. Non-engineers can print replacement parts and tools, making home maintenance more accessible and cost-effective. Entrepreneurs can rapidly prototype products by repeating designs based on accurate print predictions, thus reducing time to market. Small businesses can offer custom 3D-printed products and services, using high accuracy to ensure customer satisfaction. Reducing the number of printing errors and material waste reduces the market entry costs of companies wanting to use 3D printing technology. High accuracy makes 3D printing more profitable for non-technical business owners, expanding the market for 3D-printed goods. Artists and designers can use 3D printing to create intricate and precise works of art, pushing the boundaries of creativity. Designers can prototype and refine their creations with high confidence in the quality of the print [27–29].

4.1. Main Current Limitations and Challenges

We are currently seeing technological, financial, organizational, legal, and cultural constraints and challenges (related to both low public awareness and habits/technological culture) in the area. Overcoming these requires both time and financial investment, but the results can provide a leap towards new distribution models for sustainable and personalized additive manufacturing products and services. The consumption model of planned utility (i.e., achieving maximum profit within the initial months or years of a product's arrival on the market) is conducive to this: changing fashions and trends, where the market life of products and services is relatively short, or even pre-planned in time, as is currently the case with computer games, for example. This approach represents accepted minimalism, as citizens will consume the optimum personalized types of products and services for the length of time they find them attractive and then recycle them. The limitation is that AI methods rely heavily on high-quality data, and poor or incomplete data can lead to inaccurate forecasts and suboptimal production processes. Implementing AI in additive manufacturing can be complex and require significant expertise in both fields that may not be readily available in all organizations. Also challenging is the integration of AI systems with existing manufacturing processes and equipment, which can be difficult, requiring significant modifications and investments. AI algorithms, especially deep learning models, often require significant processing power and memory, which can be expensive. Training AI models can be time-consuming, delaying the implementation of improvements in the production process. Some AI solutions that work well on a small scale may not scale effectively to larger, industrial additive manufacturing operations. AI estimates and predictions are not always 100% accurate and may still require human oversight to validate and correct results [30–35].

In applications where production data is sensitive, ensuring data privacy and security when using AI may be problematic and require additional efforts and resources. Moreover, AI models trained on specific datasets may not generalize well to new or slightly different production conditions. Artificial intelligence models are often based on historical data, which may not take into account innovative materials or new production techniques that have not been used before. Therefore, maintaining the required high level and developing AI systems may be expensive, and in some applications even unprofitable, which potentially limits their use to larger companies with sufficient resources. Ethical concerns related to the use of AI (potential job transfer, transparency of decision-making in AI systems, etc.) cause public resistance. Some artificial intelligence methods, especially deep learning, act as "black boxes", making it difficult to understand how decisions are made and fully trust their results—it is necessary to fully introduce explainable AI.AI systems may struggle to quickly adapt to rapid changes in technology or manufacturing practices, potentially falling behind industry advances [36–38]. Also, the need to maintain compliance with industry standards and regulations may pose a challenge when implementing artificial intelligence in production and require additional validation and certification processes (cf. EU AI Act) [39,40].

4.2. Directions for Further Research

AI-based simulations can model the entire production process, predicting problems before they occur and suggesting improvements. By analyzing large datasets, machine learning algorithms can predict optimal printing parameters, reducing trial and error in additive manufacturing [41,42]. Neural network-based models can identify patterns and anomalies in real time, improving the consistency and quality of 3D-printed parts. By simulating natural selection, genetic algorithms can optimize design parameters, improving the structural integrity and performance of manufactured components. Reinforcement learning can adaptively control the printing process, learning from each layer to improve overall compilation quality [43–45]. Using high-resolution cameras, computer vision can detect defects during printing, enabling immediate adjustments to avoid costly errors. Artificial intelligence can also predict when maintenance is needed on additive manufacturing equipment, minimizing downtime and extending machine life [46–49]. AI can optimize the arrangement of materials in a given design space for maximum efficiency, leading to lighter and stronger components and less waste [50–53]. AI algorithms can automatically generate design alternatives based on specified constraints and goals, supporting innovation and creativity in product development and product families. ML can predict the properties of new materials before they are used in production, accelerating material innovation. AI can manage and optimize supply chains for additive manufacturing, ensuring timely availability of materials and components [54–57].

AI can optimize energy consumption in additive manufacturing processes, reducing costs and environmental impact. AI systems can monitor and adjust print parameters in real time to consistently maintain high quality standards, ensuring quality control throughout the production cycle, as well as throughout the lifecycle of the product and its packaging [58–60]. AI can automate post-processing steps (e.g., support removal and surface finishing), improving productivity and consistency. AI can customize additive manufacturing processes, enabling mass customization and personalized products/services in the additive manufacturing area [61–63].

5. Conclusions

An accuracy of 97.56% means that the model is precise and makes very few errors. AI methods are significantly improving AM by optimizing design, improving process and quality control, accelerating materials development, and streamlining manufacturing processes. These advances are driving the adoption of AM across industries, leading to innovative products and more efficient manufacturing processes.

AI/ML-based solutions similar to ours, once learning sets are modified or extended, are easily adaptable to other technologies, materials, or multi-material 3D printing. They also allow the creation of dedicated, ML solutions that adapt to the specifics of a production line, including as self-learning solutions as production progresses.

Combinations of breakthrough technologies such as 3D printing support with AI/ML definitely bring more advantages than disadvantages, especially in selected fields such as healthcare/medicine, business, agriculture, education, and urban development. However, only the future will show whether we have developed them in the right direction.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/app14156730/s1.

Author Contributions: Conceptualization, I.R., J.K., J.L., and D.M.; methodology, I.R., J.K., J.L., and D.M.; software, I.R., J.K., J.L., and D.M.; validation, I.R., J.K., J.L., and D.M.; formal analysis, I.R., J.K., J.L., and D.M.; investigation, I.R., J.K., J.L., and D.M.; resources, I.R., J.K., J.L., and D.M.; data curation, I.R., J.K., J.L., and D.M.; writing—original draft preparation, I.R., J.K., J.L., and D.M.; writing—review and editing, I.R., J.K., J.L., and D.M.; visualization, I.R., J.K., J.L., and D.M.; supervision, I.R.; project administration, I.R., and J.K.; funding acquisition, I.R. All authors have read and agreed to the published version of the manuscript.

Funding: Research on artificial intelligence in 3D printing is being carried out as part of the mini-grant "Applications of artificial intelligence methods in the area of additive manufacturing techniques" in the project funded by the Polish Minister of Science under the 'Regional Initiative of Excellence'. The work presented in the paper has been financed under a grant to maintain the research potential of Kazimierz Wielki University.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data are not accessible due to some of them being industrial property.

Conflicts of Interest: The authors declare no conflicts of interest.

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