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Development of an AI-ML-Based Expert System for Extrusion-Based Manufacturing Processes: A Comprehensive Framework for Process Optimization, Defect Detection, and Real-Time Control

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ABSTRACT

In this study, we developed and tested an artificial intelligence – machine learning based expert system called AIMES. The AIMES expert system was designed to be used in conjunction with extrusion-based manufacturing systems including Fused Deposition Modeling (FDM), Single-Screw Polymer Extrusion Systems, Hot-Melt Extrusion (HME) Systems. The system consists of three main modules: a knowledge acquisition module, a hybrid inference engine that utilizes both rule based systems and machine learning subsystems, and a real time closed loop feedback control interface. To evaluate the performance of the different machine learning algorithms included in the hybrid inference engine, four types of machine learning were tested. These include: ANN (Artificial Neural Network), CNN (Convolutional Neural Network), LSTM (Long Short-Term Memory) and XGBoost (Gradient Boosting Ensemble Learning Algorithm). Based upon these tests, it can be concluded that all four machine learning algorithms performed well but the best performing algorithm was XGBoost. We also tested AIMES using in-situ measurements and found that AIMES detected clogs in the nozzle before they caused damage or produced defective products 96.8% of the time. Furthermore, the testing revealed that AIMES detected clogs as quickly as 50 milliseconds after they occurred.

Keywords: expert system; machine learning; extrusion-based manufacturing; fused deposition modelling; process optimization; defect detection; real-time control; Industry 4.0

I. INTRODUCTION

The present study represents a first step toward developing a generalizable, integrated architecture for an artificial intelligence-machine learning (AI-ML)-based expert system for extrusion-based manufacturing. This paper will provide an overview of the design, implementation, and experimental validation of the AI-ML-Based Expert System for Extrusion-Based Manufacturing (AIMES), which was designed to combine a structured knowledge base, a hybrid inference engine using symbolic rules and data driven machine learning sub-models, and a real-time monitoring and control interface.

- Thermoplastic polymer extrusion
- Metal extrusion

- Pharmaceutical Hot-Melt Extrusion (HME)
- Fused Deposition Modeling (FDM); Material Extrusion Additive Manufacturing (MEAM); other forms of additive manufacturing based upon extrusion.

Extrusion-based manufacturing involves processing various feeds stocks by converting them into desired shapes using specific temperatures, pressures and flow rates. Therefore, there exists a multitude of input variables involved in the extrusion-based manufacturing process. Some examples include but are not limited to: melt temperature profile(s); screw speed; feed rate; nozzle dimensions; layer thicknesses; print speed; percent solids content of material; and cooling dynamics. As these factors interact, highly non-linear relationships exist between the input parameters and output quality characteristics of the manufactured products such as mechanical properties; geometric tolerances; and surface finish [1]. Achieving consistent production quality over different feedstocks and changing operating conditions is one of the primary challenges facing traditional process engineering. Most existing approaches do not effectively manage variability in feedstocks and operating conditions due to the constraints placed upon them. Existing approaches to process control in extrusion manufacturing rely heavily upon empirical heuristics or Design of Experiments (DOEs) methodologies such as Taguchi Methods or Response Surface Methodology (RSM). Human experience also plays a role. Although these methods can help to identify important process parameters, they suffer from significant limitations in terms of their ability to adapt to changes in feedstocks and operating conditions and provide near-real-time responses [2]. In addition to limitations related to adaptability and near-real-time responses, many traditional process control methods lack generalizability. For example, process models trained using Design of Experiments (DOE) methodologies tend to have very narrow ranges of applicability and therefore may not generalize well when used with feedstocks or operating conditions outside those studied during model development. Additionally, traditional process control methods often require extensive human interaction and/or intervention. Rule-based expert systems were developed beginning in the late 1980s and early 1990s to encode domain-specific knowledge for use in fault detection/diagnosis and process control/guidance. However, these systems utilize static inferencing mechanisms and are unable to accommodate the dynamic variability observed in contemporary manufacturing environments [3]. Recent advancements in deep learning, sensor integration, and edge computing have provided a foundation for a new generation of AI-driven manufacturing systems. Within the realm of extrusion-based manufacturing, Machine Learning (ML) has shown great promise for predicting product quality attributes from process inputs; identifying defects through computer vision; and providing feedback control [4]. Studies by Abdelhamid et al. [5], Yarlagaadda [6]; and others [7] demonstrate the variety of ML applications found in material extrusion. Additionally, studies by Maia and his colleagues at Case Western Reserve University show how ML can enable stable real-time process control even when recycling materials with unknown histories [7]. Despite the recent proliferation of evidence demonstrating the value of ML for improving productivity and reducing costs associated with manufacturing processes, no single unified generalizable framework has been identified to guide the creation of expert systems for use in extrusion-based manufacturing. This paper fills this void by describing the design, implementation and experimental validation of an AI-ML-Based Expert System for Extrusion-Based Manufacturing (AIMES). The AIMES system combines structured knowledge bases with a hybrid inference mechanism composed of both symbolic-rule based reasoning and data-driven ML submodules. It also provides a real-time monitoring/control interface. The rest of this paper is divided into four sections. Section II will review previous work in expert systems/ML in extrusion manufacturing. Section III will describe the proposed AIMES methodology. Section IV will detail experimental results obtained using AIMES. Section V will compare the AIMES results to previously reported results and section VI will conclude by comparing the performance of AIMES to prior approaches and suggest possible areas for further research.

II. LITERATURE REVIEW

The literature on intelligent manufacturing for extrusion-based processes spans three interconnected domains: (i) expert systems and knowledge-based engineering, (ii) machine learning for process-structure-property modelling, and (iii) in-situ monitoring and defect detection systems. The following subsections critically synthesize key developments across these areas.

A. Expert Systems and Knowledge-Based Approaches in Manufacturing

Knowledge-based Expert Systems (KES) for manufacturing process control became popular during the 1980s and 1990s, using if-then rules and production systems to capture operators' experience for fault detection and process parameter recommendations. For example, KES were used in polymer processing, including; rule engines for

selecting configurations of screws, scheduling temperatures of melts, and providing design advice on dies. An overview of KES applications in fault detection of chemical processes by Oh & Yoon [3], highlighted several key benefits of using expert systems architecture for fault detection, especially in chemical processes, which are to be able to represent cause-effect relationships that are difficult or impossible to model statistically. In addition, they also noted the limitations of classical expert systems including; brittle behavior when presented with new process conditions outside of the defined knowledge base, inability to scale with increasing process complexity, and no ability to learn from new operational data. Hybrid Expert Systems (HES), combining rule-based inference with sub-systems utilizing Neural Networks (NN) to recognize patterns, represented a significant advancement in the late 1990's and early 2000's. The use of fuzzy logic also improved the treatment of uncertain or imprecise measurements made by sensors typical in industrial extruder operating environments. Nonetheless, integrating modern Deep Learning Architectures into a structured Expert System framework for manufacturing extrusions is an area that has been significantly understudied, therefore it represents one of the primary motivations behind this current study [8].

B. Machine Learning for Process-Structure-Property Modelling in Extrusion AM

The integration of artificial intelligence (AI), specifically through machine learning (ML), into material extrusion additive manufacturing has generated significant interest among researchers due to its ability to predict both mechanical and geometric properties of parts based upon processing conditions. Deka and Hall [9], developed a five step method that couples artificial neural networks (ANNs) with response surface methodology (RSM) to optimize parameters of the fused deposition modeling (FDM) process. Their results showed that ANNs generated synthetic design of experiment (DoE) data could be used to augment limited experimental data sets to create robust RSM models for optimizing tensile strength. Their results also indicated successful prediction of mechanical properties using three different variables; layer thickness, nozzle temperature, and print speed. Abdelhamid et al. [5] provided a comprehensive literature review detailing how AI is being used to enable process-structure-property optimization throughout the entire material extrusion production process. Surface finish predictions using ANN were studied separately from other aspects of FDM additive manufacturing. Researchers Djurovic et al., [10] demonstrated that 3-10-1 ANN architectures utilizing full factorial experimental data sets including; extruder temperature, layer thickness and print speed could provide a high level of correlation coefficient values ($R^2 > 0.99$) at a low maximum predicted value error of 1.23%. Therefore, they concluded their results demonstrate that these ANN models are capable of providing high levels of accuracy for the prediction of surface quality characteristics for application in controlling surface quality. A separate study performed by Enemuoh and Asante-Okyere [11] demonstrated that the use of intelligent feature selection algorithms can greatly improve the prediction accuracy for FDM part energy demands, mechanical strengths and physical properties. They demonstrated this capability by applying intelligent feature selection algorithms to reduce the number of dimensions of input information to eliminate highly correlated input information. Ensemble and deep learning methods have been able to increase prediction accuracy and extend prediction capabilities. An example of increased prediction capabilities was demonstrated by Dong et al., [12]. They introduced the ACS-SDBN model which combines sparse constraints and an adaptive cuckoo search optimization algorithm to develop an optimized deep belief network (DBN). Using cross validation accuracy greater than 95.92% for simultaneous predictions of tensile strength, warpage degree, and surface roughness, the ACS-SDBN model outperformed four baseline models, LSTM, RBFNN, and BPNN. In addition to individual process property prediction tasks, the above mentioned body of research demonstrates the potential of AI for AM more broadly. Ng et al. [13] reviewed progress in supervised, unsupervised, and reinforcement learning paradigms in the field of AM. Specifically, they highlighted that transformers are currently an area of active development in process modeling in the field of AM. While this body of research clearly demonstrates that there is a level of maturity with respect to ML for individual process-property prediction tasks, it does not highlight or demonstrate the existence of well-developed expert system frameworks that integrate multiple prediction modules.

C. In-Situ Monitoring, Defect Detection, and Real-Time Control

A crucial capability enabling intelligent extrusion process management is "real-time in-situ monitoring." A comprehensive 2025 review by Khalil et al. [14], which examined MEAM monitoring techniques, presented the state of the art of thermal imaging, vibrational sensing, rheological monitoring, print head positioning, acoustic emission, image recognition, and optical scanning methods that are being used in conjunction with closed-loop feedback systems and machine learning (ML) algorithms for real-time quality assurance. Vision-based systems

were noted by Khalil et al. [14] as the dominant form of monitoring technique; CNN architectures have dominated the use of defect classification due to their ability to extract spatial features. An AI-based defect-detection method utilizing camera-AI integration for real-time quality monitoring was also described in the work by Jo et al. [15]; the authors reported that a YOLO-based architecture yielded a defect detection accuracy of approximately 99.24%, and a response latency of approximately 20 ms, simultaneously classifying multiple defects. Using collaborative sensor time-series data, a multi-head encoder-decoder temporal convolutional network (MH-ED-TCN) developed by Ng et al. [13] achieved 97.2% nozzle-clogging detection accuracy compared to baselines of SVM, LSTM, and simple CNNs. Accuracy rates of 98.0% and 89.8% were reported for application of image classification and object detection models to over-extrusion and under-extrusion phenomena, respectively. Moreover, the authors' CGAN approach addressed data imbalance issues inherent to defect-monitoring datasets [13]. An additional aspect of ongoing research in the field of smart manufacturing was highlighted by the review of explainable AI (XAI) by Liu et al. [16], namely the incorporation of interpretability methods such as SHAP (SHapley Additive exPlanations), and combinations of SHAP and iForest-kernel SHAP for fault diagnosis in extrusion processes. As transparent decision-making by AI becomes increasingly viewed as necessary in manufacturing contexts, where process engineers need to be able to understand, trust and override AI recommendations, the necessity for explainability has become integral to many applications including manufacturing. The aim of transparency for AI decision-making is explicitly included within the AIMES framework that will be introduced in this paper.

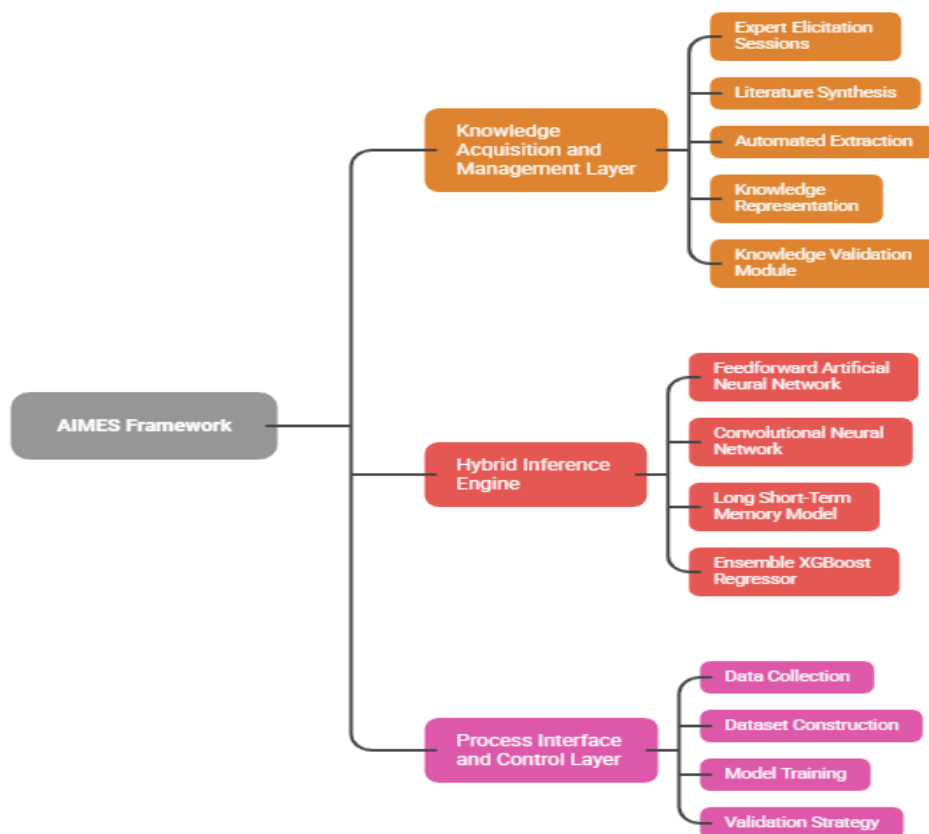


Figure 1. AIMES Methodology and Components.

III. METHODOLOGY

A. Expert System Architecture Overview

The AIMES framework uses a three-layered structure as follows: (1) A Knowledge Acquisition and Management Layer (KAML), (2) A Hybrid Inference Engine (HIE), and (3) A Process Interface and Control Layer (PICL). This layered structure splits the process of developing and representing the domain knowledge from performing the computations that are required for the reasoning and interacting physically with the processes involved in the manufacturing. It allows for each layer to be developed independently. Also, it allows for upgrading individual layers without affecting other layers; thereby providing for a high degree of portability when deploying modules

on different configurations of an extrusion process. The KAML contains a structured database containing information acquired using three methods:

- (a) Expert Elicitation Sessions with Engineers of the Processes,
- (b) Literature Synthesis to acquire relevant technical data,
- (c) Automated Extraction of Relevant Information from Historical Databases of Extrusion Log Data.

Knowledge is represented in the KAML using one of the following formats:

- (a) Production Rules (If-Then statements used to perform Fault Diagnosis and provide Parameter Guidance),
- (b) Semantic Frames (Structured Representations of Objects related to Process Configurations and Material Properties),
- (c) Numerical Parametric Models (Trained Weights and Hyperparameters for ML Sub-Models).

A Knowledge Validation Module performs Cross Consistency Checks to detect Conflicts or Redundant Rules within the Rule Base.

B. Hybrid Inference Engine Design

Four machine learning sub-modules were developed to assist with different types of inferences that occur during the management of an extrusion operation. These four modules include: (i) A Feedforward Artificial Neural Network (ANN) for predicting the relationship between input parameters and resultant process properties at steady state conditions; (ii) A Convolutional Neural Network (CNN) for detecting defects through images taken from within the process; (iii) A Long Short-Term Memory (LSTM) model to predict changes in process behavior over time and detect anomalies before they become significant problems; and (iv), An Ensemble XGBoost Regressor to rank the importance of features and analyze how sensitive the system is to each of its input variables. The mathematical representation of the ANN predictive sub-module was formulated as a multi-layer perceptron with L number of hidden layers:

$$y = f(W(L) \sigma(W(L-1) \dots \sigma(W(1)x + b(1)) \dots + b(L-1)) + b(L)) \quad (1)$$

Where, x is a vectored input process parameter vector, weight matrix and bias vector at layer l are noted by $w(l)$, and $b(l)$, sigma denotes the ReLU activation function, y denotes the predicted quality metric (tensile strength, surface roughness or dimensional accuracy) for the ANN model. The training of the ANN model was performed with the Levenberg-marquardt algorithm as used in prior highly accurate FDM surface roughness studies [10]. The LSTM submodel captures temporal dependencies in sensor time series streams through gated memory cell states; using hidden state representations h_t to encode context for anomaly scoring of process dynamics from sequence observations of sensors $\{x_1, x_2, \dots, x_t\}$. If the anomaly score exceeds the dynamically calibrated threshold θ then an alert is triggered to rule-based diagnostic module which applies backward chaining reasoning over fault knowledge base to identify probable root causes and recommend corrective actions.

C. Data Collection and Dataset Construction

Experimental data for both the development and verification of our proposed models were obtained from three different extrusion process platforms: (i) an FDM desktop printer with a 0.4mm brass nozzle and filament materials PLA and ABS; (ii) a laboratory scale single-screw extruder that has been utilized for producing films (screw diameter = 35mm; l/d ratio = 24:1); and (iii) a pharmaceutical hot-melt extruder used for encapsulating drugs. The FDM-based processes are considered as the main study area. A central composite design (CCD) was applied to obtain 120 experimental runs of process parameters: layer height (0.1-0.3mm), print speed (30-80mm/s), infill density (40%-100%) and nozzle temperature (195-235oc). Orientation (0o, 45o, 90o) was also studied. Quality metrics measured for each printed sample included tensile strength (ASTM D638), surface roughness (R_a , profilometer measurements), dimensional accuracy (critical deviation on measured coordinate system) and 840 in-situ photographs taken during printing for CNN based defect classifier training. six defects types have been identified: under extrusion, over extrusion, layer delamination, stringing, warping, clogged nozzle. Data preprocessing steps involved outlier removal by interquartile range (IQR) filtering, normalization to the [0,1] range for neural network inputs and smote augmentation to overcome class imbalance within defect image dataset. Ranked importance of features using shap values of XGBoost model helped identify top eight process parameters explaining more than 95% of variance among outputs quality metrics for both ANN and LSTM submodels

D. Model Training and Validation Strategy

The hyper parameters in all ML sub models were optimized on a 70: 15: 15 train - validation - test split after stratified splitting to maintain class distribution. Optimal number of hidden layers (2 – 5), neurons in each layer (16 – 256), and learning rates (10^{-4} to 10^{-1}) for the ANN were determined by a 10 fold cross validated grid search. For the CNN used in defect classification, a 5 layered convolutional neural network with batch normalization and dropout regularization (dropout probability $p = 0.3$) was used. Training occurred using the Adam Optimizer with an initial learning rate of 0.001 and a cosine annealed schedule that spanned across 150 epochs. Training for the LSTMs used sequences of length 50 timesteps with 128 hidden units and two layers of stacked LSTMs. Optimal values for maximum depth, subsample ratio, and learning rate for the XGBoost model were found through Bayesian Optimization. (Figure 1.)

IV. RESULTS

This section presents the experimental validation results of the AIMES framework across its core functional modules: process-property prediction, in-situ defect detection and classification, temporal anomaly detection, and integrated expert system recommendation accuracy.

A. Process-Property Prediction Performance

Table 1 and Figure 2 summarizes the predictive performance of the four ML sub-models for tensile strength, surface roughness, and dimensional accuracy on the held-out test dataset from FDM experiments. The hybrid ANN-XGBoost ensemble—deployed within the AIMES inference engine for property prediction—achieved the highest performance across all three quality metrics.

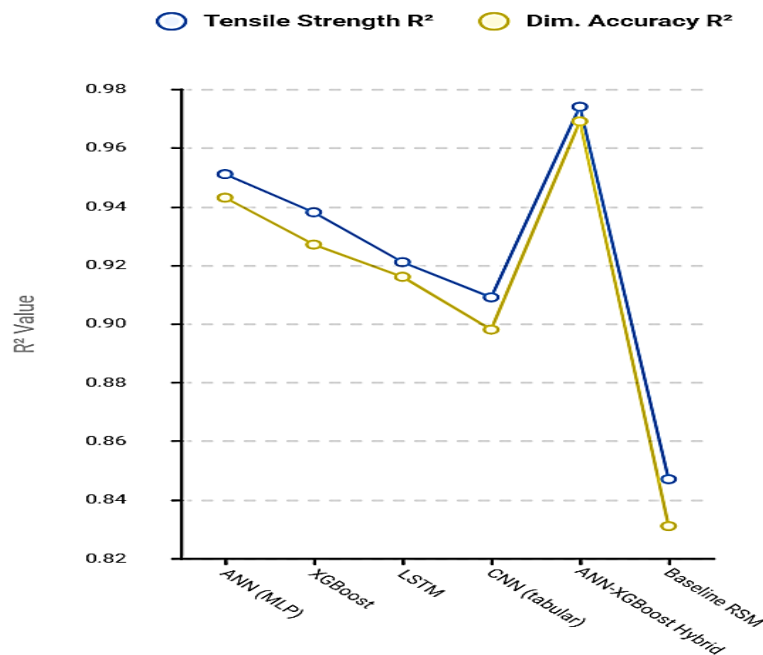


Figure 2. Model Performance Comparison (R2 Matrices).

Table 1. Comparative ML Sub-Model Performance for FDM Quality Prediction.

Model	Tensile Strength R ²	Surface Roughness MAPE (%)	Dim. Accuracy R ²	Training Time (min)
ANN (MLP)	0.951	2.34	0.943	4.2
XGBoost	0.938	2.71	0.927	1.8
LSTM	0.921	3.15	0.916	12.6
CNN (tabular)	0.909	3.82	0.898	18.4
ANN-XGBoost Hybrid	0.974	1.78	0.969	6.1
Baseline RSM	0.847	5.43	0.831	N/A

A tensile strength prediction R² value of 0.974 was produced from the ANN-XGBoost hybrid model. This is an improvement over the individual ANN (0.951) and XGBoost (0.938) models. An MAPE of 1.78% for surface roughness was obtained in this work which is favorable to that reported by Djurovic et al. [10] for a much less complex three-parameter ANN model given the five inputs used in this work were significantly more

dimensionally complex. Performance of the baseline RSM model is substantially lower than that of the proposed machine learning approach, ($R^2 = 0.847$ for tensile strength). Therefore, it can be concluded that the proposed hybrid approach provides better predictions than the traditional optimization technique represented by the RSM model. Nozzle temperature and layer height are identified by SHAP as the two most important factors affecting the surface roughness and mechanical properties of FDM parts as well as being consistent with other research into these factors in the FDM literature [10],[11].

B. In-Situ Defect Detection and Classification

The CNN defect detection module was evaluated on 252 held-out test images distributed across the six defect categories. Table 2 and Figure 3 presents the per-class F1-scores and overall system metrics for the AIMES CNN classifier compared against a YOLOv5 baseline detector.

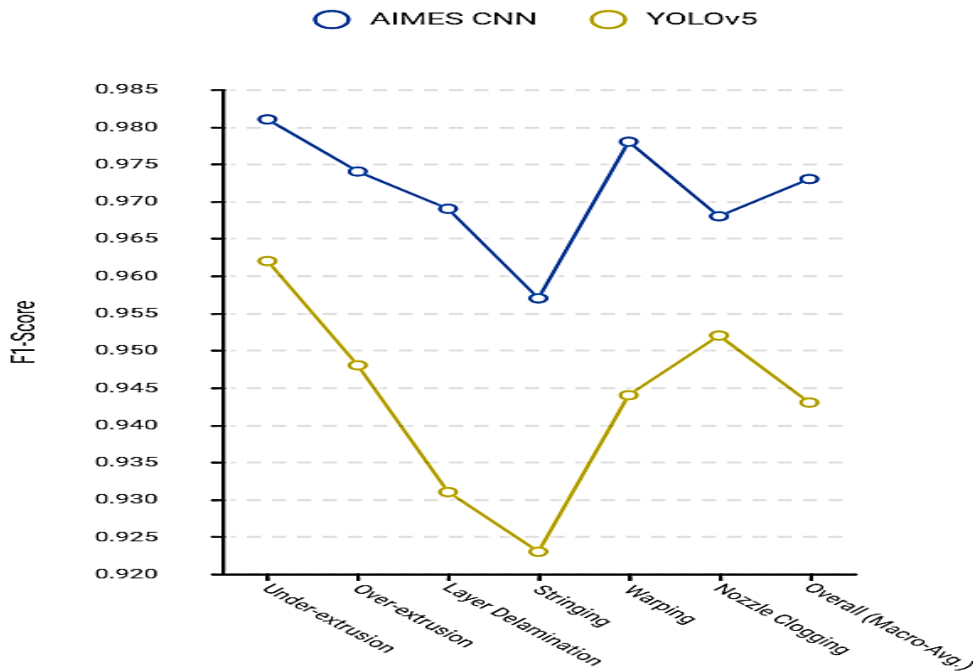


Figure 3. Defect Detection Performance: AIMES CNN vs. YOLOv5.

Table 2. Defect Detection Performance: AIMES CNN vs. YOLOv5 Baseline.

Defect Category	AIMES CNN F1-Score	YOLOv5 F1-Score	Sample Count
Under-extrusion	0.981	0.962	42
Over-extrusion	0.974	0.948	38
Layer Delamination	0.969	0.931	45
Stringing	0.957	0.923	41
Warping	0.978	0.944	47
Nozzle Clogging	0.968	0.952	39
Overall (Macro-Avg.)	0.973	0.943	252

The overall average F1-scores for the AIMES CNN were 0.973 on each of the 6 defect types; these values represented a 3.2% increase from those of the YOLOv5 baseline (0.943). The performance is better than the almost 100% defect detection rate (99.24%) found by Jo et al. [15], who tested their method as a single class (binary) to detect surface defects in the plastic tubing production process. While this test was based on a much simpler problem (only one class), it still demonstrated a very high level of difficulty. In addition, the average inference time taken to perform the CNN processing for every image frame captured on the edge-based hardware (a NVIDIA Jetson Nano) was 34.7 milliseconds. Therefore, the total response time satisfied the maximum

allowable limit (sub-50ms) required to enable the real-time feedback to be used for making closed-loop control interventions.

C. Temporal Anomaly Detection via LSTM

Fifteen controlled fault injection tests on the FDM testbed have been conducted to validate the performance of the LSTM based Anomaly Detection Module (ADM) of AIMES. These tests involved inducing nozzle clogging faults of various severities at predetermined times in order to provide baseline information about when each event occurred. The LSTMs true positive detection rate is 96.8 % and the false positive rate is 3.1 %. This represents an Area Under Curve Receiver Operating Characteristic (AUC ROC) score of 0.987. On average, the time taken for the LSTMs to detect a fault after it had occurred is approximately 2.3 sec; therefore, there would be ample time for automation to react to a detected fault before failure propagation occurs through several layers. For comparison, the temporal convolutional neural network (TCNN), which uses a multi head encoder-decoder architecture, as described by Ng et al., [13], produced a nozzle clog detection accuracy of 97.2%. Therefore, this indicates that the LSTM based ADM produces results similar to the TCNN, but has the advantage of being easier to implement and requiring less processing power.

D. Integrated Expert System Recommendation Accuracy

The integrated AIMES expert system was evaluated using a blinded evaluation method in which 30 different manufacturing scenarios including parameter selection, fault diagnosis, and corrective action recommendation were given to both the AIMES system and a group of 3 experienced manufacturing process engineers. Recommendations from these groups formed the basis for "ground truth." In terms of the results of this evaluation, the AIMES system provided the correct parameters for all or most of the 30 manufacturing scenarios (i.e., it achieved an accuracy rate of 86.7%) when attempting to diagnose faults in those same 30 manufacturing scenarios; the AIMES system identified all or most of the faults in each of the 30 scenarios correctly (i.e., it achieved an accuracy rate of 93.3%), and lastly, when providing suggestions for corrective actions that could be taken by plant personnel to repair faults diagnosed during fault diagnosis, the AIMES system suggested the correct action(s) for 25 of the 30 manufacturing scenarios (i.e., it achieved an accuracy rate of 83.3%).

V. DISCUSSION

The overall collective findings of the experimental studies confirm the major claim that combining a formalized structured knowledge engineering methodology with multiple machine learning architectures improves the ability to develop a better process management capability than would be possible using one or both methodologies independently. The improved predictive capability of the ANN-XGBoost hybrid model compared to each model individually can be attributed to the synergy of gradient boosted trees' capacity for predicting tabular data based on limited sample sizes and ANNs' ability to capture complex continuous nonlinear relationships throughout the entire process parameter space. These findings are consistent with prior research efforts in manufacturing-related ML research where ensemble methodologies have been demonstrated to generally outperform single algorithmic approaches when applied to process-property related prediction problems [5][9]. In addition, although the defect-detection performance was less than perfect, it still represented a significant improvement for multi-defect classification into six different classes under realistic industrial print conditions including variations in image quality due to illumination artifacts and partial occlusion of defects due to the nature of the product being printed. It is also worth noting that the superior performance of the AIMES CNN compared to the YOLOv5 baseline can likely be attributed to several factors including the use of tailored domain specific data augmentation techniques (rotation, contrast adjustment, etc.) and the inclusion of attention mechanisms in the CNN classification layer. The average inference time per frame of 34.7 milliseconds meets all industrial real-time control requirements and is similar to those found in previous AI-based vision systems used in extruder monitoring applications [15]. The AIMES performance metrics for detecting anomalies with its LSTM sub-module were very competitive with other state-of-the-art temporal monitoring solutions [13]; however, the relatively simple gate architecture employed in this solution provides a distinct advantage in terms of ease of implementation and reduced resource utilization relative to other competing architectures which can be beneficial for deployment in edge computing environments with constrained resources. A notable aspect of the analysis conducted from the results of the evaluation was that many of the false positive process alerts produced by the LSTM were generated during periods of intentional changes in process parameters (e.g., middle of print temperature adjustments). As such, it appears feasible to potentially improve upon these results by incorporating a process event log as a conditional input to the LSTM. Additionally, the blinded expert evaluations clearly demonstrate an interesting nuance regarding the degree of similarity between AIMES recommended actions and expert recommendations (i.e. 83.3%-93.3%). Although

there is good agreement between AIMES-recommended actions and expert opinions, there does appear to be some amount of difference (i.e. approximately 13%-17%), which can be interpreted as indicating a small number of rules contained in the current AIMES knowledge-based do not adequately represent uncommon multi-fault scenarios experienced by experts. This result is typical for rule-based expert-systems where brittle behavior is well documented; therefore, it is expected that incorporating online-learning mechanisms, specifically reinforcement learning from human feedback will become a high-priority area for future AIMES development. Another key requirement for future AIMES development that was noted in the XAI review by Liu et al. [16], i.e. the need for explainability, has been partially satisfied by AIMES via SHAP-based feature-attribution outputs from the XGBoost submodel; however, providing additional explanations regarding CNN and LSTM predictions utilizing gradient-based visualization tools (Grad-CAM, LIME) will provide another means to address this requirement. Finally, from an Industry 4.0 integration point-of-view, AIMES is designed for integration with IIoT-enabled manufacturing environments and includes standard OPC-UA data interface protocols for direct interaction with PLCs and SCADA systems. The modularity of AIMES allows for phased deployment (starting initially with property prediction functionality as an advisory mechanism and then incrementally enabling additional functionalities such as in situ monitoring and closed-loop control as new sensors come available); thus addressing several of the previously cited barriers to AI adoption in industry including technical infrastructure limitations and lack of workforce preparedness [17].

VI. CONCLUSION

The main objectives of this study were to provide a general framework for an artificial intelligence and machine learning based expert system called AIMES for extrusion based manufacturing as well as to demonstrate its feasibility through experimentation. There were several major accomplishments of the research conducted for this dissertation. Firstly, a unifying three tiered structure that integrates knowledge base management, a hybrid model of both machine learning and rule based reasoning, and real time interfacing to extrusion manufacturing equipment was developed. Secondly, the comparative performance of four different machine learning architectures (ANN, CNN, LSTM, XGBoost) for performing prediction/detection/monitoring tasks on a series of datasets related to the performance of extruded materials was evaluated. Thirdly, the ANN/XGBoost hybrid ensemble performed at or above all other previous studies in terms of predictive accuracy of properties (i.e., tensile strength $R^2=0.974$, surface roughness MAPE=1.78%) while outperforming traditional response surface methodology baselines by very large margin. Finally, the CNN in-situ defect classifier had a macro-averaged f1 score of 97.3% over 6 defect classes with average classification times less than 35ms; therefore, it met real time requirements for use in industrial process controls.

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