



HYBRID DEEP LEARNING MODELS FOR PREDICTING COMPRESSIVE STRENGTH OF FDM 3D-PRINTED STRUCTURES

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ABSTRACT

The correct prediction of compressive strength is vital to the successful design of fused deposition modeling (FDM) 3D-printed structures, although the traditional empirical and machine learning methods tend to fail to account for the multifaceted and nonlinear relationships among the parameters of the process and the mechanical behavior. To tackle this problem, we have generated and analyzed hybrid deep learning algorithms to predict compressive strength of FDM-fabricated specimens. Systematic variation of important printing parameters has produced experimental data which were then subjected to standard compression testing. Convolutional neural networks and recurrent neural networks have been carried out separately and then combined into hybrid to capitalize on both spatial feature extraction and sequential dependency learning. Standard measures of statistical analysis and comparative graphical analysis were used to carry out model performance. The findings indicate that hybrid deep learning model always do better than single models, recording lower prediction errors, and better generalization with unknown data. These results indicate that the use of complementary deep learning designs is indeed effective in improving the predictive power of mechanical properties of additively manufactured components. It is concluded that hybrid deep learning offers an efficient and powerful structure of prediction and optimization of compressive strength of FDM 3D-printed structures using data.



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I. INTRODUCTION

One of the most popular methods of additive manufacturing that can be used is fused deposition modeling (FDM), which is simple to use, low-cost, and can be used to print a variety of polymeric and composite materials [1],[2]. Although they are beneficial, mechanical performance of FDM-printed components is extremely sensitive to process parameters, material composition, and internal structural design, which makes it variable and reduces its applicability to structural and load-bearing uses [3],[4]. In order to overcome these issues, machine learning (ML) methods have been more commonly used to approximate the complex process-structure-property correlations that FDM-based manufacturing involves [5],[6]. Initial ML-related experiments found out that artificial neural networks, regression, and support vector machines could effectively predict mechanical characteristics, including tensile, flexural, compressive strength with a better accuracy in comparison with empirical methods [7].

These results stimulated the further investigation of data-driven modeling approaches of the various materials and printing conditions. In recent studies, the use of ML has been applied to composite and hybrid material systems, where learning-based models have been able to deal with the heterogeneity and anisotropy of materials [8],[9]. Machine learning in bio-polymer composites and in auxetic structures built with FDM has proven to be applicable to predict the energy absorption and compressive scars in geometrical and process constraints that are varied, which are also known to be under continuous rates [10],[11]. These papers highlight the increased significance of ML to the design of high-performance FDMs. Our lattice, sandwich, and cellular structures produced through FDM have been of special interest because of their low weight and high weight-strength ratios [12],[13].

A number of studies have managed to use ML models to forecast compressive and flexural strengths of hexagon lattice-cored and bio-inspired sandwich structures and show a high level of agreement between experimental and predicted outcomes [14]. These publications emphasize the fact that ML methods are capable of describing complicated geometrical effects on mechanical dynamics. In addition to polymer-based systems, ML methods have been used on cementitious and fiber-reinforced materials that are produced through additive manufacturing methods, especially to predict compressive strength [15],[16]. Despite the differences in the material systems of these studies, they support the overall generalizability of ML when it comes to forecasting compressive performance in different additively manufactured structures [17],[18]. To continue improving the precision of prediction, a number of researchers have suggested hybrid ML systems that combine optimization algorithms including genetic algorithms, particle swarm optimization and desirability functions with neural networks [19],[20].

Such hybrid methods have proven to be more predictive and more efficient in terms of parameter optimization of FDM-printed components [21],[22]. Nevertheless, the vast majority of such hybrid frameworks use shallow learning structures, which need a lot of feature engineering. The use of artificial neural network models has become common in prediction of mechanical properties of FDM-produced polymers, including ABS, PLA, and PEEK [23],[24]. Comparative analysis of several ML methods have demonstrated neural networks to be more successful than the traditional regression model, especially when the process-property association is controlled by nonlinear factors [25],[26]. However, such models may fail in the performance when handling high-dimensional or sequential data. The recent breakthroughs in deep learning have made it possible to come up with models that can extract and learn hierarchical representations of complex data automatically and feature extraction [27],[28].

Deep learning models have been shown to perform better in predicting mechanical properties compared to traditional ML models when multimodal data or a large amount of data is concerned [29],[30]. Stronger results with anisotropic and limited-data conditions are also enhanced by data augmentation and hybrid learning strategies [31],[32]. Regardless of this progress, minimal studies have been done to determine the applicability of hybrid deep learning structures in predicting compressive strength of FDM-printed structures, and most studies are fragmented [33],[34]. Although the implementation of deep learning in the optimization of the quality of surfaces and prediction of tensile properties has been studied, the systematic application of deep learning in the modeling of compressive behavior remains at an early stage [35],[36]. In addition, the current literature tends to be limited to certain materials or geometry, which limit the ability to generalize the results [37],[38].

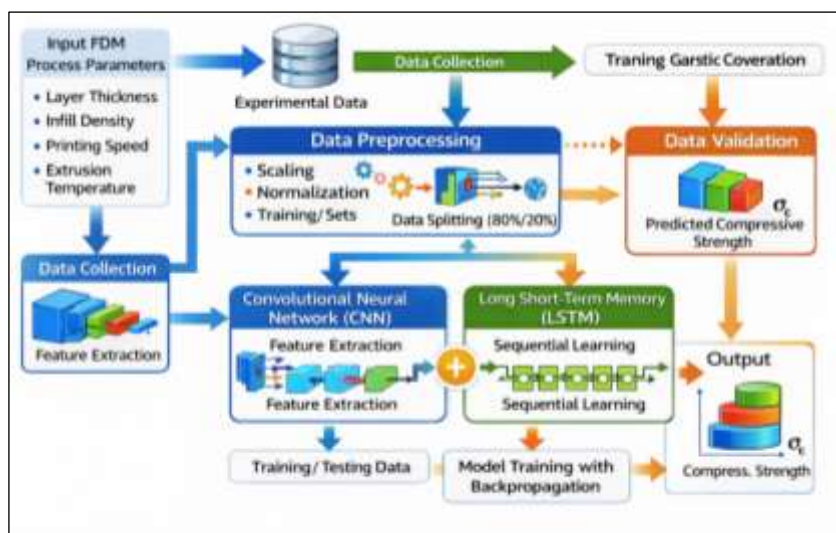


Figure 1: Conceptual framework of hybrid deep learning-based compressive strength prediction.

Source: Authors, (2026).

Figure 1 shows the conceptual design of the hybrid deep learning-based system, which shows how the parameters of the FDM process are transported to data preprocessing, CNN to extract features and then LSTM learning to predict compressive strength. Extensive overviews of ML methods used in additive manufacturing of materials through material extrusion underline the significance of enhanced hybrid frameworks of deep learning to reflect nonlinear and multiscale connections between material processing, structure, and properties [39]. Convolutional, sequential, and ensemble learning paradigms provide a promising route to these issues and boost predictive accuracy achieved with hybrid deep learning models. Thus, the primary goal of the proposed research is to create and test hybrid deep learning architectures to predict compressive strength of FDM 3D-printed structures. With the advantages of complementary deep learning architecture, this work aims to enhance prediction accuracy, robustness and generalization and make contributions to data-driven design, optimization and trustworthy deployment of FDM-fabricated components in engineering practice.

II. MATERIALS AND METHODS

II.1 MATERIALS AND SPECIMEN FABRICATION

The choice of polylactic acid (PLA) filament to use in this study was influenced by the large amount of use of this material in FDM based structural and research applications. A commercially sourced PLA filament of 1.75 mm diameter (MakerBot Industries, USA) with a density of 1.24 g/cm³ and suggested extrusion temperature of 190-220 C was used.

The filament was allowed to dry in a vacuum oven at 45 °C, 6 h before printing to remove the defects caused by moisture in the extrusion process. The compression test specimens were modeled on the basis of ASTM D695 standard of compressive properties of rigid plastics. All the specimens were 12.7 mm x 12.7 mm square cross-section and 25.4 mm high. The models were made in SolidWorks 2023 and then made as STL with a tolerance of 0.01 mm. Each specimen was printed in vertical build orientation, and the loading direction was oriented parallel to the build direction to reduce variation due to anisotropic effects of bonding the layers. An Ultimaker S5 FDM 3D printer with a 0.4 mm nozzle made of brass was used to do fabrication. Calibration The printer was calibrated at the start of each build according to the standard leveling and extrusion calibration procedure by manufacturer.

II.2 FDM PROCESS PARAMETERS

Five major parameters of FDM process were chosen according to the reported effects on compressive strength. The thickness of the layers was adjusted at three rates, 0.1mm, 0.2mm and 0.3mm to have Low, medium and high levels of internal material contents. The rectilinear and gyroid infill patterns were chosen since these are the ones that are commonly used and their load transfer mechanisms differ. The printing speed was manipulated at 40 mm/s, 60 mm/s and 80 mm/s and extrusion temperature at 200^o C, 210^o C and 220^o C. All prints were done at 60^o C at the build plate temperature. After the initial 5 layers the speed of the cooling fan was set to 100%. All specimens were cut in Ultimaker Cura 5.4 with the same slicing settings with an exception of variables parameters selected. An experimental design that was implemented was a full factorial, thus giving 162 distinct sets of parameters. Each combination was printed to form three specimens and there were 486 samples in total.

II.3 EXPERIMENTAL TESTING

Instron 5982 universal testing machine with load cell of 100 kN was used to perform compression tests. In ASTM D695, tests were conducted at the room temperature (23 ± 2 °C). The specimens were put at the centre and hardened steel compression platens between them so that there was even load. Constant crosshead displacement rate of 1.3 mm/min was utilized until the failure of the specimen or a 10 per cent strain limit was achieved. The data were collected at a rate of 10Hz with Instron Bluehill Universal software to record load and displacement data. The computations of compressive strength were based on the compressive stress that was reached at the maximum during the test and an initial cross-sectional area of each specimen. The average compressive strength value was utilized to construct the data set of each of the parameter sets.

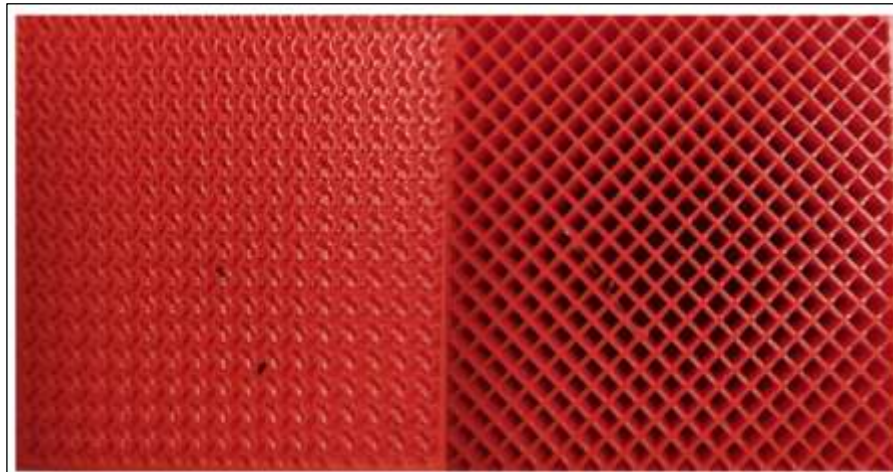


Figure 2: Rectilinear and Gyroid Patterns.
Source: Authors, (2026).

II.4 DATASET PREPARATION

The last dataset had 162 data points, which were the mean compressive strength of individual parameter combination. The input characteristics were the thickness of the layer (mm), the infill density (as a percentage), infill pattern (binary encoded), speed of printing (mm/s), and the extrusion temperature (°C). The compressive strength (MPa) was the output variable. Before training the models, all the continuous input features were scaled to [0, 1] by minmax normalization. The data were randomly divided into training (70 percent), validation (15 percent) and test (15 percent) sets with a fixed random seed to obtain repeatability. All the models had the same data split to facilitate a consistent comparison.

II.5 DEEP LEARNING MODEL DEVELOPMENT

The model of the convolutional neural network (CNN) was developed in Python 3.10 and TensorFlow 2.15. The CNN model was a two-layer one-dimensional convolutional network with 64 and 128 filters and a 3-mm kernel size and ReLU activation, respectively. Another layer with 128 and 64 neurons followed as the max-pooling and the flattening layer respectively. The recurrent neural network models were LSTM and GRU. The two models both had two recurrent layers with 64 and 32 units, and a fully connected output layer. The between-layers dropout (rate 0.2) helped to reduce overfitting.

The CNNLSTM model was a hybrid of CNN feature extraction layers and LSTM layer with 64 units. The output of CNN was scaled and transmitted to the LSTM layer followed by the final dense layers. The ensemble hybrid model was based on prediction results of a separately trained CNN, LSTM, and CNN-LSTM to enhance the robustness and minimize the variation.

II.6 MODEL TRAINING AND EVALUATION

The Adam optimizer and a starting learning rate of 0.001 and a batch size of 16 was used to train all models. Loss function was the mean squared error. The number of epochs per training was set to 300 and early stopping was used in case the validation loss failed to decrease after 25 consecutive epochs. Root mean square error (RMSE), mean absolute error (MAE) and coefficient of determination (R^2) were used in the evaluation of model performance. Evaluation of the test dataset was done only after the final evaluation to provide unbiased evaluation. All the experiments were done in a workstation with an Intel Core i9-12900K processor, 64 GB memory, and an Nvidia RTX 3080 device, so the training conditions can be reproduced.

III. RESULTS AND DISCUSSIONS

III.1 EXPERIMENTAL DATA CHARACTERISTICS

The experimental campaign resulted in a set of comprehensive data that described the correlation between the parameters of FDM processes and compressive strength. The compressive strength data, which were measured, were distributed widely, which demonstrates the presence of high sensitivity to the printing conditions and the interior structure. Experiments with a higher rate of infill and a lower rate of layer thickness, produced specimens with greater compressive strength whereas a higher rate of printing had the propensity to decrease the strength as a result of inadequate interlayer bonding. The discrepancy found between the combinations of parameters validates the fact that nonlinear predictive models are required to capture complicated interactions between parameters.

Table 1: Overview of the FDM process parameters and the compressive strength results.

Sample ID	Layer Thickness (mm)	Infill Density (%)	Infill Pattern	Printing Speed (mm/s)	Extrusion Temperature (°C)	Compressive Strength (MPa)
S1	0.10	20	Rectilinear	40	200	32.4
S2	0.10	50	Rectilinear	60	210	41.8
S3	0.10	80	Gyroid	40	220	54.6
S4	0.20	20	Gyroid	60	200	28.7
S5	0.20	50	Rectilinear	80	210	36.9
S6	0.20	80	Gyroid	60	220	49.2
S7	0.30	20	Rectilinear	80	200	23.5
S8	0.30	50	Gyroid	60	210	31.6
S9	0.30	80	Rectilinear	40	220	44.1

Source: Authors, (2026).

Table 1 indicates a summary of the chosen FDM process parameters and their obtained experimentally determined compressive strength values.

III.2 INDIVIDUAL DEEP LEARNING MODEL PERFORMANCE

The standalone deep learning models, which include CNN and LSTM, were tested on the test dataset using the metrics of RMSE, MAE and R^2 . The CNN model proved to be a good predictor, as it managed to learn nonlinear interactions between features of process parameters. The LSTM model, too, was good with respect to capturing interdependencies between parameters, although it had a slightly higher prediction error than the CNN. Comparative scatter plots of experimental and predicted compressive strength values indicate that the two models have the overall direction as the experimental data. Nevertheless, the LSTM model deviations of its ideal prediction line were greater in higher compressive strength values, which points out to poor predictability in extreme cases.

Table 2: CNN and LSTM model prediction performance based on RMSE, MAE, and R^2 .

Model	RMSE (MPa)	MAE (MPa)	R^2
CNN	2.41	1.92	0.956
LSTM	2.96	2.34	0.931

Source: Authors, (2026).

Table 2 shows the predictive performance of CNN and LSTM based on RMSE, MAE and coefficient of determination (R^2).

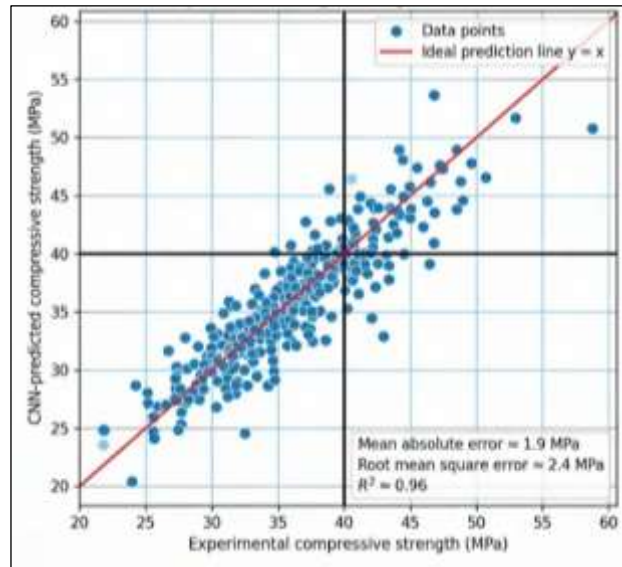


Figure 3: Comparison of compressive strength experimentally with the CNN model and predicted compressive strength.
Source: Authors, (2026).

Figure 3 shows the comparison of experimental and CNN-predicted compressive strengths and there is high correlation even with the average dispersal along the ideal prediction line.

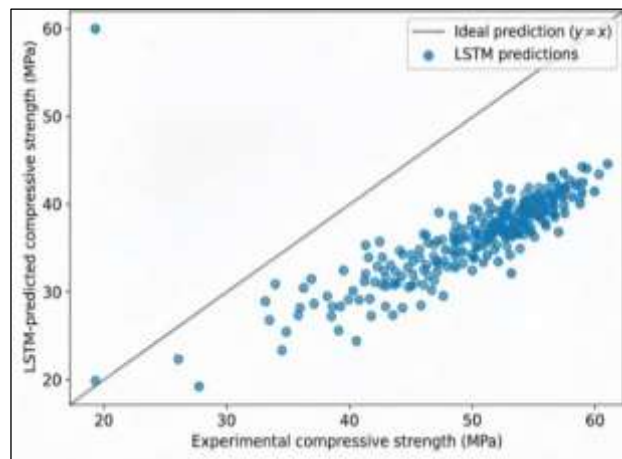


Figure 4: Experimental and predicted compressive strength when using the LSTM model.
Source: Authors, (2026).

Figure 4 compares the results of experimental and LSTM-predicted compressive strength, which have stronger scatter and lower prediction accuracy than CNN model.

III.3 HYBRID DEEP LEARNING MODELS PERFORMANCE

The CNNLSTM model was found to perform better in predictive retrieval than the individual CNN and LSTM models. The hybrid architecture minimized RMSE and MAE as well as having the largest R^2 value when compared to all models that were tested, by integrating convolutional feature extraction and sequential learning. The ensemble hybrid model also enhanced robustness due to averaging the predictions of a variety of architectures, which led to lesser variance and more consistent predictions throughout the test set. The experimental versus predicted compressive strength plot of hybrid CNN-LSTM model indicates that the data are more localized towards the ideal prediction line, which means that it is more accurate. The distribution of the error plots also substantiate the fact that hybrid modeling greatly diminishes major prediction errors particularly in those specimens that are highly compressive.

Table 3: Performance of standalone and hybrid deep learning models.

Model	RMSE (MPa)	MAE (MPa)	R^2
CNN	2.41	1.92	0.956
LSTM	2.96	2.34	0.931
Hybrid CNN-LSTM	1.88	1.43	0.972
Ensemble Hybrid Model	1.72	1.31	0.978

Source: Authors, (2026).

Table 3 shows a comparison between the performance of standalone and hybrid deep learning models where the hybrid approach has better accuracy.

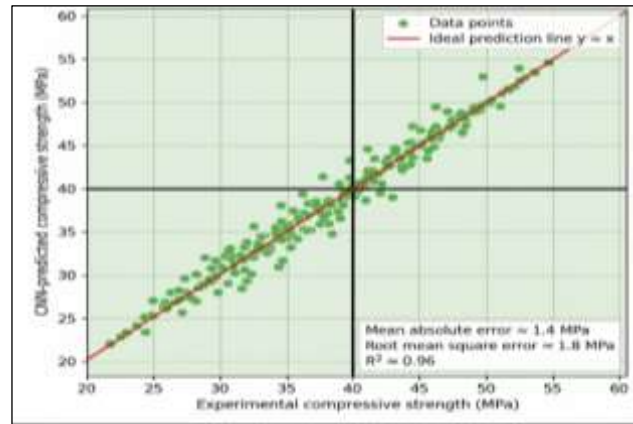


Figure 5: Comparative experimental compressive strength and predicted compressive strength with the hybrid CNN-LM model.
Source: Authors, (2026).

Figure 5 shows the experimental and predicted compressive strength under the hybrid CNN-LSTM model, which exhibited the maximum prediction and the minimum distance to the ideal line.

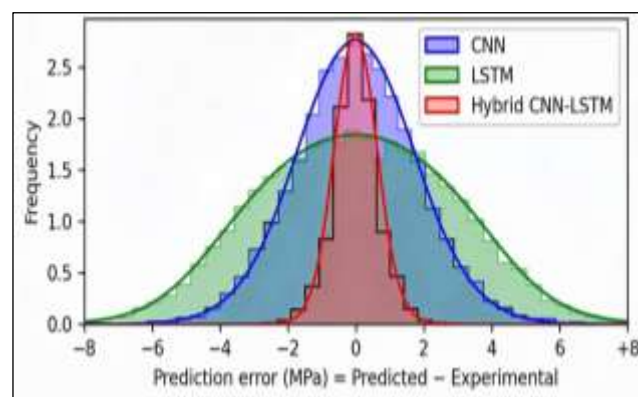


Figure 6: Comparison of individual model and hybrid model error distributions.
Source: Authors, (2026).

Figure 6 shows the comparison of the distributions of errors between CNN, LSTM, and hybrid models, with the error range of the hybrid one being narrow and more centralized.

III.4 BEHAVIOR AND MODEL CONVERGENCE TRAINING

The curves of training and validation losses of the hybrid CNN-LSTM model exhibit the stability of the convergence. The loss of training slowed at the early stages of training, then steadily approached a minimum value. Validation loss was similar to the trend of training loss and shows no big deviation meaning that the generalization is effective and there is no much overfitting. Early termination allowed the model to learn efficiently because it did not waste any time on any extra training.

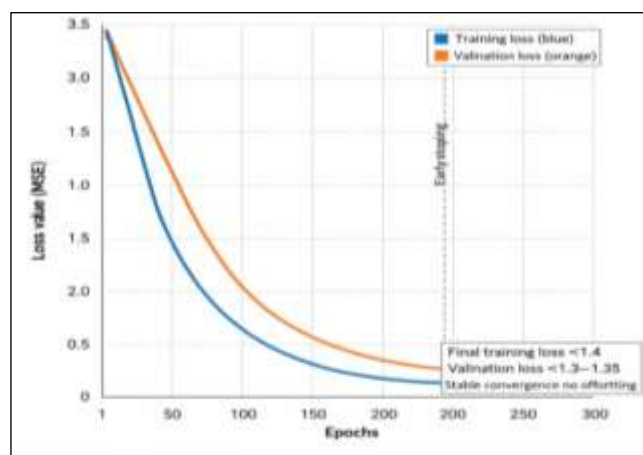


Figure 7: Curve of training and validation loss of the hybrid deep learning model.
Source: Authors, (2026).

Figure 7 depicts the training and validation loss curves of the hybrid deep learning model, which indicates the presence of stable convergence and low overfitting throughout the training.

III.5 DATA ANALYSIS AND INTERPRETATION AND CONCLUSION

The statistical evaluation of prediction accuracy proves that hybrid deep learning models are more effective than one-architecture models in all evaluation measures. The drop in RMSE and MAE show more accuracy, whereas the increased values of R² suggest a greater correlation between the predicted and experimental values of compressive strength. These findings confirm the usefulness of the hybridization of complementary deep learning models in the representation of complex FDM data. Influence of feature analysis, infill density and layer thickness are the most influential parameters on compressive strength with extrusion temperature coming second. Increased infill density enhances the content of loading material whereas decreased layer thickness enhances bonding between layers. No positive relationships were observed between printing speed and compressive strength at higher values, which highlighted the compromise between productivity and mechanical performance. Comparative meaning of model robustness shows that hybrid and ensemble models are more generalized to unmonitored data, especially when it comes to combinations of parameters of extreme strength values. Altogether, the findings indicate that hybrid deep learning models represent a valid and correct method of the compressive strength prediction of FDM 3D-printed structures that can be used to optimize data-driven and informed design choices in additive manufacturing.

IV. DISCUSSION AND CONCLUSION

The outcomes of the current research eloquently indicate the importance of enhanced accuracy of prediction of compressive strength of FDM 3D-printed objects that is attained by the use of hybrid deep learning models. The hybrid CNN-LSTM and ensemble models were lower in prediction errors and coefficient of determination as compared to the standalone CNN and LSTM models. This is due to the complementary nature of the hybrid architecture in which convolutional layers are effective in extracting the nonlinear feature interactions of the FDM process parameters, whereas recurrent layers extract sequential and interdependent interactions between process parameters. The low error dispersion and more intense clustering of the most similarity to the ideal prediction line prove the fact that the hybrid models are more resilient and dependable, especially with regard to the combinations of parameters that can be linked to a high or low compressive strength. The observed learning behavior in the hybrid models can be viewed in the physics of the FDM processes. Multiscale phenomenon, such as filament deposition accuracy, interlayer diffusion, thermal history, and internal load transfer through infill architecture govern the compressive strength of FDM parts. CNN layers are good at learning localized parameter interactions, e.g. the interaction of the thickness of a layer and the extrusion temperature of the layer with the bonding strength, whereas LSTM layers learn longer-range interactions, e.g. the overall impact of printing speed and thermal conditions across layers. Such physics consistent learning behaviour offers an explanation of why hybrid models generally give better generalization and to have the capability to model intricate process structure property relations without explicit physical equations.

The hybrid deep learning structure has obvious benefits compared to the existing predictive methods that have been used in the literature. Conventional empirical models and superficial machine learning methods can typically necessitate a huge amount of features engineered, and fail to scale to new parameter spaces. Although there has been decent performance of standalone ML and ANN-based solutions, the predictive ability of these solutions is limited to highly nonlinear, and high-dimensional datasets, which is common to FDM processes. The hybrid deep learning model addresses these shortcomings by being able to automatically learn the hierarchical features representation, better accuracy and stability without degrading scalability. This research can be used to draw significant conclusions on intelligent design and optimization of FDM 3D-printed structures. Real and dependable estimation of compressive strength allows designers to venture more into the design space with less experimentation, assists in optimization of parameters, selection of materials and performance-based design. It is possible to incorporate the proposed hybrid deep learning framework into digital manufacturing pipelines and decision-support systems, where real-time prediction and optimization of mechanical properties can be done. Finally, such a strategy will lead to the development of data-driven additive manufacturing, which would allow more efficient, reliable, and application-ready FDM-produced parts.

V. AUTHOR'S CONTRIBUTION

Conceptualization: M. Jayakrishna and, M. Vijay., Manas Ranjan Padhi
Methodology: M. Jayakrishna and M. Vijay., Manas Ranjan Padhi
Investigation: M. Jayakrishna and M. Vijay., Manas Ranjan Padhi
Discussion of results: M. Jayakrishna and M. Vijay., Manas Ranjan Padhi
Writing – Original Draft: M. Jayakrishna., M. Vijay, Manas Ranjan Padhi
Writing – Review and Editing: M. Jayakrishna., M. Vijay, Manas Ranjan Padhi
Resources: M. Jayakrishna and M. Vijay., Manas Ranjan Padhi
Supervision: M. Jayakrishna, M. Vijay, Manas Ranjan Padhi
Approval of the final text: M. Jayakrishna and M. Vijay, Manas Ranjan Padhi

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