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ENERGY CONSUMPTION PREDICTION IN 3D PRINTING USING ENHANCED HYBRID DEEP LEARNING MODELS

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ABSTRACT

The 3D printing method is characterized as an energy-intensive technology with a major negative influence on the ecosystem and sustainability. Since then, both business and academics have turned their attention to the problem of 3D printing energy usage modelling, prediction, and optimization. However, prediction of energy consumption is a common issue in 3D printing. Thus, this research aims to forecast the energy consumption in 3D printing employing a novel Convolutional Neural Network with Long-Short Term Memory (CNN-LSTM). The developed model has five stages: data collection, data augmentation, pre-processing, feature extraction, and prediction. In data collection, Ender-3 pro 3D printer data were collected; whereas, in pre-processing, data normalization was performed by min-max normalization and missing data imputations was carried out using Mean or median. Moreover, feature extraction was done using Principal Component Analysis (PCA) method. Furthermore, in prediction phase, CNN-LSTM is employed for forecasting the energy usage. Moreover, the model's performance has been evaluated in regards to Mean Square Error (MSE), correlation, Root-MSE (RMSE), Normalized-MSE (NMSE), and Mean-Absolute Error (MAE). Furthermore, comparison has been performed to identify the effectiveness of the presented model over other methods.

I. INTRODUCTION

The manufacturing sector remains crucial to the growth of the world economy via jobs, social engagement, and economic power. Nevertheless, manufacturing operations also have a negative influence on the surroundings, compensating for a significant amount (nearly 90%) of manufacturing power usage and CO2 emissions as 84%, which present significant problems for the globe in the present era, including biodiversity loss, resource scarcity, and global warming [1]. Moreover, for the years to come, it is anticipated that the world's energy consumption would rise. The primary source of the increased CO2 emissions that causes increase in sea levels and climate changes seems to be the fossil fuels combustion. After decades of decarbonization efforts, conventional fossil fuels remain account for 84.7% of global energy use.

Since its introduction in the earlier 1990s, additive manufacturing (AM) or 3D printing processes have advanced, grown more sophisticated, and changed the way things have been created and planned. Layer-by-layer manufacturing processes allow for the development of operationally stratified materials, the manufacture of components with complicated geometries, and the reduction of material waste. From becoming an instrument for testing to gradually being used for end-part manufacturing, it has gone a lengthy ways. To print actual functional components from numerous types and materials shapes, a number of fabrication methods have been created, including selective laser-melting (SLM), stereo-lithography (SLA), laser-engineered net-shaping (LENS), fused filament-fabrication (FFF), and selective laser-sintering (SLS). AM methods give component designers a good chance to generate a variety of parts because to their considerable design flexibility for generating end-use components.

Yet, the great level of design flexibility in manufacturing also makes the AM method more challenging in regards to intricate mechanical systems and distinctive design elements. A solitary AM manufacturing process may also create many parts simultaneously in certain multiple-part manufacturing techniques, including SLS and SLM. The anisotropic character of the components, porosity owing to inadequate fusing between nearby filaments, and deformation as a consequence of residual tension as an outcome of the AM procedure's quick cooling nature have been specific difficulties to be solved. It is essential to have a thorough grasp of the link among the printing settings and the resultant microstructures and AM component's material characteristics, along with the feedstock material's process ability (powder flow-ability and rheological properties).

The AM procedures, nevertheless, involve a number of process variables that may have an impact on the reliability of the finished parts, necessitating a thorough knowledge of a number of fields, including thermal-mechanical engagement, fluid dynamics, solid-liquid engagement, grain innovation, and material characteristics. In addition, AM demonstrates the importance of treating and refining material qualities of goods with reduced material usage and enables quick product fabrication from concepts [2]. As a result, AM is used in a extensive range of commercial and institutional settings, comprising automotive, aerospace, and dentistry equipment [3]. Thought has been given to the emerging environmental worries about durability, in specific about energy usage [4].

Consequently, it is critical to improve power consumption in AM equipment. Thus far, this element has received increasing scrutiny from manufacturers and scholars. AM had the ability to provide a higher product yield, which would increase energy consumption. Earlier on in the production chain, eco-design is required to assist manufacturers and engineers with decision-making, energy management, and process enhancement [5]. Yet, because the AM sub-systems provide so much information during the procedure, it is difficult to enhance energy management. Furthermore, material jetting, powder-bed fusion, vat photo-polymerization, Direct-Energy deposition (DED), sheet lamination, binder spraying, and material expansion are the seven classifications into which AM techniques are often divided [6].

Several technologies were created for every AM procedure to fulfil the growing need for printing capabilities in regards of design, materials, and effectiveness. Energy management concerns are becoming increasingly important for sustainable manufacturing as industrial AM technologies have been used by more sectors [7]. The complexity of an AM technology, nevertheless, makes it difficult to analyze and estimate its energy usage because it often consists of numerous subsystems with various sub-procedures. If the system's energy usage could be anticipated prior to the start of the procedure, methods for increasing energy efficiency may be developed. Hence, for improved energy regulation in the AM sector, it is essential to unearth energy-related facts and create precise prediction frameworks.

The industrial procedures energy efficiency is thought to be directly connected to both external variables and the process variables [5]. Moreover, computerized simulations have been a crucial component of AM development and optimization, since they save costly manufacturing procedure trial and error. Prior employing AM to create the desired part, finite element-predicated multi-physics simulation models (FEM) [8] have been built to mimic the AM process. FEM-based computations, nevertheless, take a lot of time and money to run. This gives rise to the drive to create a machine learning (ML)-based prediction tool, which can instantly provide the simulation outcome rather than doing pricey physics-based computations.

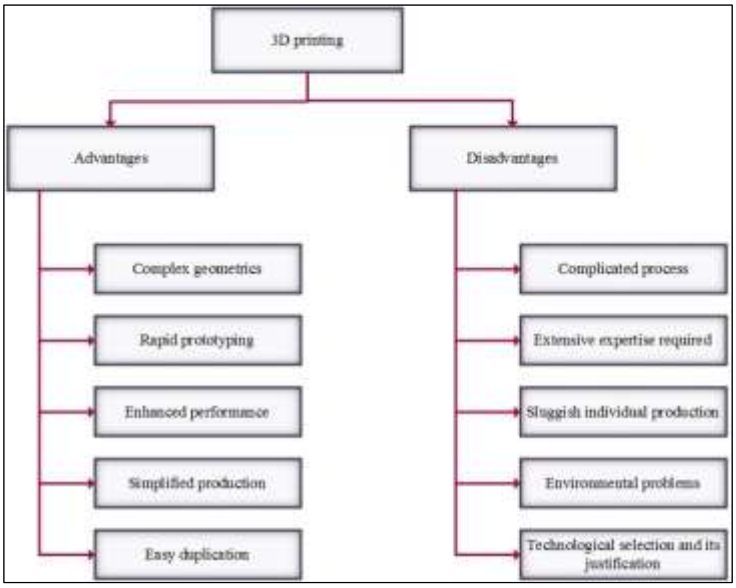

Figure 1: 3D printing Pros and Cons.
Source: Authors, (2026).

AM introduces a new manufacturing framework that produces tangible components by stacking materials in accordance with digitalized 3D models generated by computer-aided design (CAD) tools. The design possibilities of a design have been increased and the manufacturability has been enhanced by this free-form production method [9], [10]. Using a solitary 3D printer, it is possible to produce parts with specialized and intricate forms, accomplishing free-form production and eliminating the drawbacks of conventional manufacturing processes. In recent decades, additive manufacturing (AM) has demonstrated a significant promise for clean environmental and energy-saving operations because of mitigation in resources and material use and other equipment needs [11]. More information on AM procedures is now available thanks to the advent of data detection and gathering technology. The use of sophisticated data analytics methods to enhance energy management tactics has also increased.

The key important issue has been to retrieve and gain significant energy-relevant statistics and comprehension from this input from the present AM machines, which have been frequently integrated with various sensing equipment where there has been a tremendous quantity of data created during AM operations. Following that, the decision-making procedure is carried out using the data's information that has been retrieved [12]. When modelling with fixed structure, like neural networks, there is a trade-off among model reduction and effectiveness, therefore it's important to keep performance degradation to a minimum while preserving computing resources. The pros and cons of 3D printing are shown in Figure 1.Computational intelligence (CI) applications need to find solutions to the drawbacks of 3D printing.

This is particularly true when it comes to enhancing the fundamental printing processes by utilizing expertise from several fields such as 3D printer technologies, design and software engineering, and materials science. Overall else, the following have been necessary to find creative solutions to them: familiarity with material characteristics and interaction both during inside the object and printing; 3D printing innovation and material selection for a particular interface; design specifications for a particular printed artifacts; and parametric optimization [13], [14]. However, an AM technology often consists of numerous subsystems that each requires a separate sub-process, making it challenging to analyze the system's power usage. Thus, this research aimed to develop a novel hybrid deep learning (DL) for predicting the power consumption in 3D printing. The key contribution of the present work is described as follows:

- Initially, 3D printing model's data like filament size, printing time, width, build speed, depth, and height are gathered.
- Hereafter, data augmentation process is performed to expand the training set by leveraging existing data to create updated duplicates of a database.
- Then the augmented data undergoes pre-processing in which the process done includes duplicate data removal, data normalization, and missing data imputation.
- Moreover, the features required for prediction are extracted using Principal Component Analysis (PCA).
- Finally, hybrid CNN-LSTM approach is presented, which predicts the energy consumption in 3D printing.

II. RELATED WORKS

AM represents a paradigm change in regards of operational adaptability and product customization, demonstrating considerable potential for industry-wide adoption. AM seems to be a rapidly growing innovation for rapid production. Because to the rising needs and uses of AM technologies in manufacturing, energy usage has recently drawn more interest in research and market. The energy usage of AM technologies, which are divided into multiple subsystems and are thought to be very complex, seems connected with a number of different aspects. These parameters come from numerous sources and frequently include properties of multiple kinds and dimensions, making it difficult to integrate them for analysis and modelling. By [15] presented a hybrid ML method to manage this multi-source information with distinct granularities and frameworks for forecasting energy usage in order to address this problem. This method integrates the density-based spatial clustering of applications with noise (DBSCAN) and extreme gradient boosting (XGBoost) method.

The article takes into consideration four distinct elements, namely working environment, design, method, and material. In order to decrease data complexity, the unorganized data has been grouped by DBSCAN and merged with custom attributes into the XGBoost algorithm for forecasting energy usage. To show the viability of the suggested approach, a case scenario that concentrated on the real-world SLS technology has been carried out. The findings showed that, like an ensemble learning method, XGBoost offers a workable method to forecast energy usage in a sophisticated AM system. Unfortunately, as a result of the lack of a feature extraction method, the projected and actual value exhibits a sizable discrepancy following prediction. In turn [16] looked at the design-relevant elements first in terms of energy modeling. Before manufacturing, process operators and part designers often decide on these aspects.

With the use of design-relevant data analysis, AM energy usage understanding that is concealed in the design-relevant characteristics is leveraged for predictive modeling. An innovative DL-driven particle swarm optimization (DLD-PSO) approach has been suggested to mitigate the energy consumption on the basis of the new modeling methodology. DL is used to improve the worldwide optimum of PSO and solve a number of concerns, including speeding up search times. Lastly, a case example is shown to test the suggested modelling technique, and the findings demonstrate its benefits, utilizing the design-relevant information gathered from a real-time AM technology in manufacturing. To help part manufacturers and process administrators rethink their plans and choices and lower the energy usage of the chosen AM technology under consideration, optimization was additionally conducted. However, the processing time is lengthy.

According to [17] used an ML-based technique to investigate various geometrical parameters at each printing phase and connect them to the mask image projection SLA's energy usage. By using layer-wise geometrical data from the design phase, the created frameworks would be capable of offering AM architects a practical tool for calculating power usage and raise knowledge of cleaner manufacturing in AM. Appropriate features have been chosen and/or retrieved from layer-wise geometric properties and utilized in the research to learn and evaluate ML models. The stacked autoencoders (SAE) architecture seems to have the highest testing effectiveness with 0.85% mean-RMSE, while the deep neural network does have 0.75% least mean RMSE (including both training and evaluation). Also, the DL approach performs better in testing than the neural network approach and regression approach, and it would be extremely useful in actual industrial situations.

However, additional environmental sustainability indicators, such as material use and operational emissions, have been not examined. AM has made it increasingly successful in the last ten years because the ability to produce functional components with complicated geometries quickly using methods like 3D printing and laser metal casting, which would be challenging to do with conventional machining. Computational methods were employed to mimic the performance of AM procedures prior to the trial run since the expense of producing a complex component for a costly metal like titanium becomes prohibitive. To forecast the AM procedures behavior, physics-informed data-driven ML algorithms are extremely helpful, but simulations have been time-consuming and operationally expensive for forecasting multi-scale multi-physics occurrences in AM. Such concepts enable real-world control techniques employing in-situ data along with multiscale simulation instruments.

Consequently, in order to create a data-driven method-based real-time control mechanism, [18] have created and built key elements of a methodological architecture. The dataset is created and time-dependent thermal equations have been solved using FE techniques. With the use of a computer program, the computer may be programmed to perform a variety of tasks, like calculating the time required to finish a task, calculating the number of steps required to finish a task, and more. The models estimate temperature distributions for AM procedures with an MAE of less than 1%. Although the focus of this study has been on temperature profile forecasting for an AM procedure, incremental forming cannot use the same concept. In the realm of manufacturing, AM seems to be a new manufacturing method that has the ability to manufacture complicated components and has great material usage, yet it additionally faces the issue of enormous energy usage, which has aroused worry.

The energy usage dispersion of AM apparatus has still been unexplored in the present study, which mostly concentrates on the AM energy usage procedure and its effects on the surroundings. By categorizing the apparatus into various energy units, [19] provided an analytical approach for resolving the AM equipment's energy usage distribution. The energy usage and dispersion of several AM equipment kinds, such as fused deposition modeling (FDM), SLA equipment, and SLM, have been studied in particular. The suggested energy usage quantification approach predicated on energy units has been then used to machine a typical structure in attempt to study the energy usage distribution features of the 3 distinct AM machines. The findings shown that the suggested technique can rapidly and accurately forecast how much energy AM machine will use. A procedure optimization technique taking energy usage and formation quality into account is given to achieve the best process variables for FDM predicated on the energy usage distribution approach.

This technique can enable the forecast of energy usage and the enhancement of AM's energy productivity. However, each energy unit's energy usage is not optimized. Although AM offers several benefits than subtractive manufacturing techniques, one of its main drawbacks was surface integrity. By [20] provide a data-driven forecasting modelling strategy to forecasting surface roughness in AM to enhance the additively built component's surface integrity. Heat and vibration information is gathered using a variety of sensors, includes infrared temperature sensors, accelerometers, and thermocouples. For the purpose of developing the surface roughness prediction framework, an ensemble learning approach has been presented. Features inside the frequency and time dimensions have been retrieved from sensor-based circumstance monitoring data. To increase the effectiveness of computing and the precision of predictions, a subgroup of these traits is chosen.

The circumstance tracking data gathered from a series of AM tests carried out on an FFF machine has been used to validate the prediction model. The suggested predictive modelling technique may accurately forecast the 3D printed element's surface roughness, according to experimental data. Nevertheless, this model cannot be modified to forecast the additively made component's surface roughness. The environment's constrained potential and the natural resource's depletion have made the sustainability challenges more urgent. Being the cornerstone of human civilization and society, production is crucial to sustainability. Layer-by-layer item fabrication is a novel method of production that offers a possible alternative to conventional subtractive manufacturing. The AM's sustainability performance hasn't been calculated or assessed, however, in a satisfactory manner. Most energy consumption research on AM in the research nowadays focuses on establishing links between process variables and power use.

Although these researches can help with integrated process engineering and ecological sustainability, they don't link product design to sustainability effectiveness, which limits their predictive power. As a result, they can't be utilized directly to help the creation and redesign of products. Moreover, connecting the needed power usage with the item shape can help with the creation of a life-cycle inventory dataset for AM operations. In attempt to assess and forecast the mask image representation SLA procedure's energy usage, [21] employed an innovative ML-based technique to extract geometry-related characteristics. The research's findings will be a crucial component of models for unit production processes and add to the AM's life-cycle inventory by addressing the disparity between process energy and usage product geometry. However, the computational time is high. The importance of attaining sustainable manufacturing continues rising as environmental consciousness and environmental legislation are being prioritized.

AM is a desirable method for creating environmentally friendly production. Unfortunately, a universal approach to predict the AM's energy usage is absent due to the variety of AM kinds and the varying working conditions of machines' parts. In order to anticipate energy usage, [22] created a novel model that took into account the energy of each part, the duration of each operation, and the functioning status of each element. A common AM method called FDM has been chosen to show how well the suggested model works. In comparison to the particular energy paradigm and the procedure-based power consumption approach, it has been discovered that the suggested framework had greater prediction accuracy. The suggested model may be quickly incorporated into the software to view the energy usage and printing time of each procedure in each element and, moreover, to serve as a benchmark for synchronizing the improvement of element quality and power usage.

However, the forecast method did not account for the time wanted for unfilled travel or the speed and nozzle's motion deceleration during the printing step. SLM's applications have been growing as a potential AM technique. Nevertheless, the SLM procedure consumes a lot of energy because of the intricate structures of SLM equipment and their slow processing speeds. For an effective assessment and decrease of SLM power use, energy prediction is essential. However, the SLM processes energy consumption is challenging to anticipate because to the variety of SLM equipment’s and their numerous working states. A unique technique to predict the SLM procedure's energy consumption was given by [23]. The power and temporal modeling of equipment sub-systems and sub-processes, respectively serve as the foundation of the suggested methodology. Prediction accuracy may be significantly increased by determining the operational conditions of SLM equipment components in each sub-process.

To show the viability of the suggested approach, two instances of aluminum components produced by an SLM process employing an SLM 280HL machine have been chosen. The suggested technique performs better in energy usage predictions than particular, stage-predicated, and subsystem-predicated energy benchmark methods, according to the findings. Nonetheless, the multi-laser machine's product geometries, laser jump duration, and scan automation remain unaffected. An essential, intriguing, yet difficult challenge in smart manufacturing was how to accurately anticipate energy usage in the 3D printing. In turn [24] presented a new deep network called 3DPECP-Net to handle this issue. In order to comply with the lower energy requirements of the programs to combat energy deficit and global warming, this work is crucial.

The multisource information is divided into three components, comprising pixel-, processing-, and motion-source, in accordance with the smart energy usage modelling for 3D printing. The suggested 3DPECP-Net, in contrast to existing alternatives, is capable of successfully fuse necessary statistics in 3D printing, carrying complementary information's full benefit of various data inputs for more precise prediction. Existing approaches, on the other hand, either only leverage the CAD model's geometric characteristics or simply incorporate the processing variables into the forecasting. To capture global spatial data and local attribute details, the multisource fusion frame (MSFF) layers numerous convolutional and transformer blocks. In addition, researcher suggested a continuous attention memory network (CAMN) to effectively retrieve and retain the consistency across layers, pushing the learning of a comprehensive depiction for 3D printing energy usage forecast. Using an internal dataset, several tests are run, and the outcomes showed that the suggested 3DPECP-Net overtakes state-of-the-art techniques in aspect of prediction effectiveness. However, the processing time of the method is high.

For the creation of components with a near-net form, laser-aided AM (LAAM) seems to be a crucial metallic 3D printing and reprocessing technique. To assess and improve the distribution of residual pressure and deformation that results, it is crucial to examine the thermal field that is created by various scanning procedures. Nevertheless, utilizing a current numerical framework to simulate the multi-bead layering method in order to assess and choose the best laser scanning tactics is highly computationally costly. In order to produce training information for a physics-based ML system, [25] make utilization of a newly formed and experimentally confirmed effective thermal field forecasting mathematical method for LAAM. To determine the relationship among laser scanning sequences and their accompanying thermal history dispersion, an integrated Recurrent Neural Networks (RNN) with Deep Neural Networks (DNN) (i.e., RNN-DNN) framework has been created. The presented RNN-DNN method can then estimate the thermal field for any shape employing a variety of scanning techniques. The RNN-DNN forecasts and the outcomes of the mathematical simulation demonstrated high concordance of greater than 95%. However, this method is not performed for multi-layered 3D-deposition procedure.

III. METHODOLOGY

The main purpose of the presented work has been to forecast the energy consumption in 3D printing. The presented method contains five major steps: data collection, data augmentation, data pre-processing, feature extraction and prediction. The PCA method is utilized for the feature extraction stage. Moreover, CNN-LSTM is employed for energy consumption prediction. The developed workflow is outlined in Figure 2.

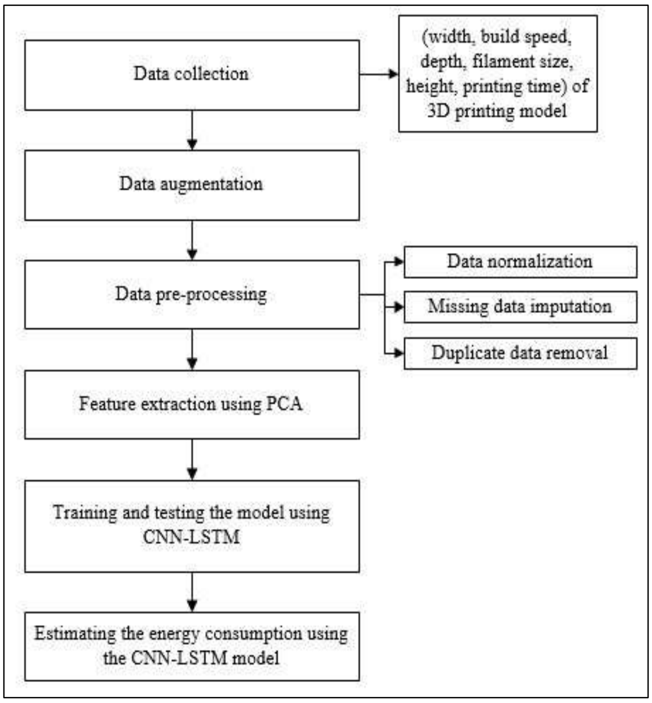

Figure 2: Workflow of presented research.
Source: Authors, (2026).

III.1 DATA COLLECTION

The intended 3D printing model has been employed to obtain the source data, in which the filament size, printing time, width, build speed, depth, and height are gathered. The data of Ender-3 pro 3D printer was used in this research. Design specifications for each tier, which have been frequently chosen at the outset of the whole process, are typically included in the information gathered from CAD drawings produced by designers.

III.2 DATA AUGMENTATION

The size of the corpus is necessarily an important attribute for a proper machine translation and the prediction of energy usage which is given as input. It helps in the development of an efficient data-driven procedure. For this purpose, the augmentation process is carried out in the study. In data analytics, procedures called "data augmentation" have been employed to expand the amount of information by introducing slightly changed versions of either existent data or brand-new artificial data that is derived from existent data.

While training a DL network, it functions as a classifier and aids in lowering overfitting. It has been strongly connected to data analytics oversampling. Moreover, by generating additional and divergent occurrences for training databases, data augmentation aids DL methods perform enhanced and yield better outcomes. A DL approach performs best and becomes more reliable if the database has been large and adequate. Moreover, Data Augmentation has been carried out while the original training set has been too small, to mitigate operating costs associated with identifying and cleansing the original database, to increase model reliability, and to avoid methods from overfitting.

III.3 DATA PRE-PROCESSING

The data have been pre-processed using a created framework and min-max normalization. Data stream mining techniques that may be used to prepare knowledge include knowledge normalization. In order to change the random number that correlates to the data, the values are raised until they fall within the predetermined points, like within 1.0. The Min-Max normalization approach has been employed to accomplish linear transformation beginning with the first stage. A rate of g of b is converted into g' within the range $[new_{\min(b)}, new_{\max(b)}]$ by min-max normalization. The component produces tuples with unfinished data by recommending among the numerous options, like majority, mean, constant, minimum, and variance, before performing the normalization technique to the supplemented data. The min-max normalization has been determined by applying Equation (1).

$$g' = {[g - \min(b)] \times [new_{\max(b)} - new_{\min(b)}]} \Big/ {[\max(b) - \min(b)]} + new_{\min(b)} \tag{1}$$

Here, $\min(b)$= attribute's minimum value, and $\max(b)$= attribute's maximum value. Equation (2) represents the formula mitigated for identifying the social control.

$$g' = {g - \min(b)} \Big/ {\max(b) - \min(b)} \tag{2}$$

A minimum and maximum normalization, or min-max normalization, upholds the relationship between the quantities of the original data.

Duplicate data removal: The divide between the training, verification, and testing sets may be destroyed by redundant data when comparable items are not all contained in a single set. This might lead to erroneous performance forecasts that let the framework down in terms of actual outcomes. As a result, the superfluous information is removed.

Missing data imputation: By replacing the missing data in the databases with another number, imputation appears to be a method for keeping the bulk of the information stored in a database. Since it's impractical to erase information from a database after each session, several techniques are used. By doing this, the size of the dataset will be drastically reduced, raising concerns about discrimination and leading to erroneous analysis. Mean or median interpolation substitutes all occurrences of missing data within a statistic with the parameter's mean or median.

III.4 PCA-BASED FEATURE EXTRACTION

To perform a full and rigorous analysis of the problems, a number of affecting factors should be evaluated in empirical studies. Yet, it gets significantly more challenging as the information assessment process grows more sophisticated. As the data provided by some inter-correlated components might overlap, the original information's relevant data might be expressed with fewer variables to decrease the level of complexity in the feature space. In accordance with this concept, Karl Pearson developed PCA in 1901, and Harold Hotelling independently came up with and updated it in the 1930s [26]. Based on the orthogonal transformation, PCA converts the possibly connected characteristic features into a distinctive group of completely uncorrelated data, referred as principal components. The number of primary components is either equivalent to or less than the original characteristic variables. Before to beginning the CNN-LSTM technique, PCA has been used to reduce the amount of data and produce a benchmark for swiftly making a prediction. The PCA's execution is defined as follows:

When a statistical framework $r \in D^q$ with q distinctive parameters and N occurrences is provided, it transforms into a completely other set of data $w \in D^h$:

$$w_{y,1} = (c_{11}\, r_{y,1} + c_{12}\, r_{y,2} + \cdots + c_{1q}\, r_{y,q}), (w_{y,2} = c_{21}\, r_{y,1} + c_{22}\, r_{y,2} + \cdots + c_{2q}\, r_{y,q}) \ldots\ldots (w_{y,r} = c_{r1}\, r_{y,1} + c_{r2}\, r_{y,2} + \cdots + c_{rq}\, r_{y,q}) \tag{3}$$

$$Here, \forall r_y = \left(r_{y,1}, r_{y,2}, \ldots\ldots, r_{y,q}\right)^t \in r, \qquad y = 1,2,\ldots\ldots,N \tag{4}$$

Every succeeding element does have the largest variance possible within its own set of limitations after the initial primary component $G_1 = w_{1,1}, w_{2,1}, \ldots\ldots, w_{N,1}$, which has the highest variance possible within the limitation that renders it transverse to the following components. The following are indicators of the PCA characteristics:

$$Variance(G_1) \geq Variance(G_2) \geq \cdots \geq Variance(G_h) \tag{5}$$

$$Covar(G_a, G_b) = 0, a \neq b, a, b = 1,2,\ldots\ldots,h \tag{6}$$

Where the $h \times q$ matrix k specifies the $y-th$ rows and a distinct coordinate structure and $k_y = k_{y1}, k_{y2}, \ldots \ldots, k_{yq}$ actually makes up element $y-th$ of the information covariance matrix M.

$$M = \frac{1}{N}\sum_{r=1}^{N} r_j r_j^t \tag{7}$$

In order to solve the characteristic formulation, PCA first computes the covariance matrix M:

$$Mk_y = \gamma_y k_y, \qquad y = 1,2,\ldots,h \tag{8}$$

Obtaining the related eigenvectors of the eigenvalues as well as the eigenvalues $\gamma_y(j = 1,2,\ldots,h)$. The eigenvector with the largest eigenvalue, G_1, which represents the most variation in the dataset r, makes up the initial component. This has been accompanied by the eigenvector with the second-largest eigenvalue, G_2, and so on. It might organize the eigenvalues in descending order and then choose the initial h main components to represent the real data in attempt to lessen the database size while keeping as much data as feasible.

III.5 CNN-LSTM BASED ENERGY CONSUMPTION PREDICTION

The CNN seems to be the deep neural network. Its objective is to identify the fundamental and inherent properties through the guided analysis of 2- or 3-dimensional data. These features have been suitable for predicting and identifying energy consumption in 3D printing. In a typical CNN architecture, an input layer is connected to several dense layers, fully-connected layers, pooling layers, an output layer, and a convolutional layer.

III.5.1 Convolutional Layer

This layer performs a convolution procedure using the raw input information and convolution kernels to produce new attribute variables. The approach was developed to extract attributes from a database; hence, the incoming data has to be structured into a matrix. The convolution kernel was already conceptualized as a tiny aperture that, in comparison to the input arrays, organizes coefficient values into a column. Convolutions are being performed on each layer while the display "slides" over the input arrays. A feature parameter called a convolved structure has been created by the filter's assigned dimension component and coefficient values. Applying different convolution operation to the input data will generate convoluted features, which have been frequently more helpful than the primary characteristics of the source data. Thus, the method works enhanced. The premise of CNN seems to be a convolutional layer, since the large number of calculations has been finished at this layer. It seems to be a data extraction stage that uses filters to extract local features, creates a feature map computed using convolution, leaves kernel function, also moves on to the pooling layer. Equation (9) contains convolutional layer expression.

$$P_m{}^{(a)} = \sigma(G_m{}^{(a)} + \sum_{n=1}^{s(a-1)} P_n{}^{(a-1)} * U_{m,n}{}^{(a)}) \tag{9}$$

Here, * (operator) represents convolution operation and $U_{m,n}{}^{(a)}$ represents filter linking the n^{th} feature-map in a-1 layer with the m^{th} feature map in a layer seems to be the function, which is utilized enhance nonlinearity, and activation matrix is denoted as σ.

III.5.2 Pooling Layer

Generally, pooling layer has been implemented after the convolutional layer. The information in the outcome of the convolution layer must be streamlined by the pooling layer. Moreover, the convolutional layer's feature map information from each feature map is used by the pooling layer to develop a condensed feature map. The most widely used strategies are mean and maximum pooling. On this stage, no learning has been taking place. In this level, size M×M filters were employed. Eqnuations (10) and (11) illustrates the average pooling and maximum pooling layers, correspondingly.

$$\bar{a} = \frac{1}{L}\Sigma_{(m,n)\in G} a_{m,n} \tag{10}$$

$$a_{max} = max_{(m,n)\in G}(a_{m,n}) \tag{11}$$

Where $a_{m,n}$ represents the quantity of each data in portion G and L denotes area's data count.

III.5.3 Dense Layer

The LSTM approach has been used in the dense layer. A subtype of recurrent neural networks with the ability to learn over time by using feedback links is the LSTM neural networks [27]. This technology generates STM and gets statistics from it utilizing cyclic linkages on their hidden layers and gather data from both time-series and sequences. Each LSTM unit consists of a memory cell as well as the three main gates for input, output, and forget.

This framework allows the LSTM to select the data that should be "forgotten" and the data that should be "remembered," resulting in a governed data stream and training for long-term interconnections. Equation (12) forecasts the LSTM unit's effective functioning. The developed approach's layers are given in Figure 3.

$$a_u = \sigma(P_u m_s + R_u n_{s-1} + t_u) \tag{12}$$

Here, weight matrices are R and P, m_s indicates input, σ represents the sigmoid function, and t denotes bias-term vector.

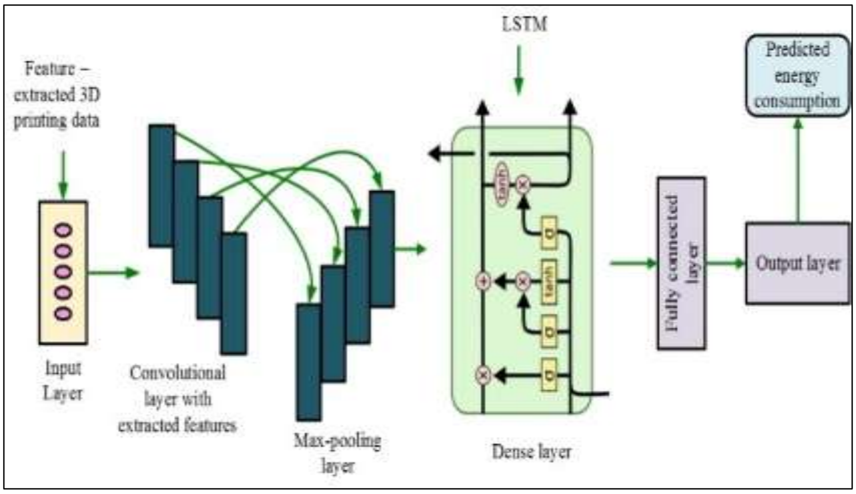

Figure 3: Developed CNN-LSTM's layers.
Source: Authors, (2026).

III.5.4 Output Layer

The output layer's cells, also referred to as the fully-connected layer, are totally dependent on all areas of the preceding layer of the memory. Behind this layer, information is turned into a 1-D array. The total number of completely linked layers in each design may vary. In this level, feed forward has been accomplished using Equation (13).

$$a_m^s = \sum_n u_f^{s-1} v_n^{s-1} \tag{13}$$

Here, number of layer is represented as s, v_n^s represents number in the developed output layer, number of neuron is represented as m and n, u_f^(s-1) indicates hidden layer's weight, v_n^(s-1) denotes input neuron and a_m^s denotes activation function's value in the output layer. The overall process of work is shown in algorithm 1.

Algorithm 1**:** CNN-LSTM

Input: Ender-3 3D printer data
Output: Energy consumption
Import input 3D printer data
Let X be the source data, which is considered for assessment
$X = \{X_1, X_{2,} X_3 \ldots.\}$
Data augmentation
Pre-processing //Min-max normalization, mean or median
Feature extraction //PCA
Initialize the CNN
Dense layer //LSTM
Prediction //CNN-LSTM
Predicting: 3D printer's energy usage
end if
end while
end

Source: Authors, (2026).

IV. RESULTS AND DISCUSSIONS

This section evaluates the suggested hybrid optimization with DL-based energy consumption performance and compares with conventional approaches. The outcomes of the simulation have been achieved for different models using different performance measures in order to evaluate the suggested DL model-based prediction's effectiveness.

Table 1: Parameter setup.

Parameters	Values
Molding method	FDM
Nozzle diameter	0.0004m
Model	Ender-3 pro
Printing size	0.22×0.22×0.25 m
Speed	50mm/s
Machine size	0.44×0.42×0.465 m
Printing precision	±0.1mm
Net weight	6980g
File transfer	SD-card offline or online
Filament	PLA
Printing temperature	210°

Source: Authors, (2026).

The suggested technique has been applied in MATLAB R2022b, and the experimental outcomes were obtained. The parameters employed for implementation is shown in Table 1. Moreover, the input models given for energy consumption prediction are shown in Figure 4 (a) and (b).

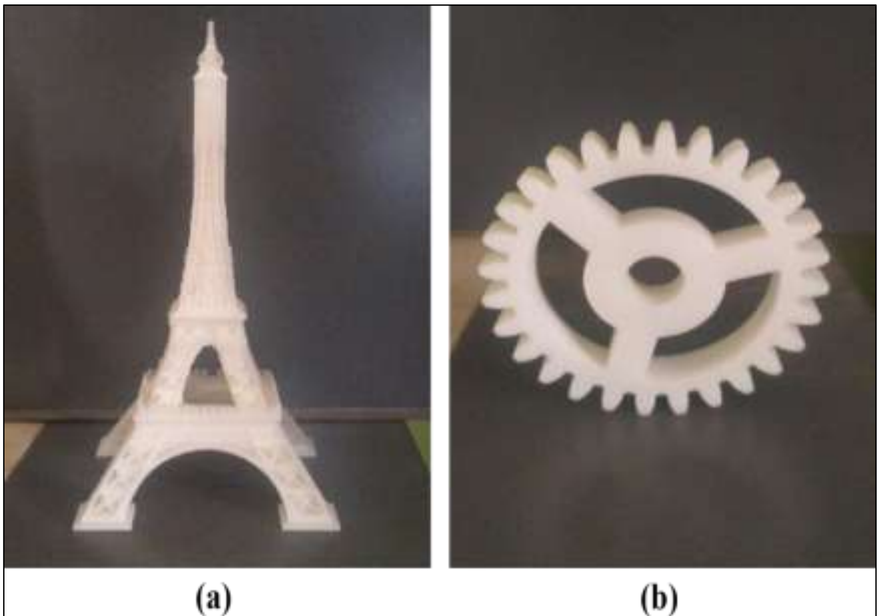

Figure 4: Input models (a) Eiffel tower (b) Gear.
Source: Authors, (2026).

IV.1 OTHER DL MODELS EMPLOYED FOR ASSESSMENT

IV.1.1 GRU

GRU is indeed a form of RNN, which was created by [28] as a simplified option to LSTM networks. GRU can analyze sequential data, including time-series data, text, and speech, just as LSTM. The fundamental principle of GRU would be to dynamically modify the network's hidden layer at each iteration interval via gating techniques. Information flow into and out of a system is managed by the gating procedures. The update gate and the reset gate are two of the GRU's 2 gating systems.

IV.1.2 CNN

In order to handle data with a grid pattern, like images, CNN seems to be a form of DL model that has been motivated by the structure of animal's visual cortex. From lower- to higher-level structures, CNN has been designed to continually and aggressively gather spatial categories of attributes. A typical CNN is made up of three different types of layers: fully-connected, convolution, and pooling layers. Convolution- and pooling-layers in order each and two provides features extraction, whereas a fully-connected layer in order multiple transforms the obtained characteristics into the consequence, such forecasting. A convolution layer appears essential in CNN that is composed of a series of mathematical operations, comprising convolution, a particular form of linear component [29].

IV.1.3 LSTM

LSTMs are employed in the area of DL. A number of RNNs, particularly in issues involving sequence forecasting, are susceptible of acquiring long-term connections. In addition to solitary data sources like images, LSTM also has feedback links that let it to analyze the whole data stream. This is useful for speech recognition and machine translation, among other things. The LSTM is a special type of RNN that excels at solving a variety of problems.

IV.1.4 Bi-LSTM

Two LSTMs—one receiving the input towards the forward manner while the second processes it in a backward direction—combine to form the Bi-LSTM, a sequential processing paradigm. With the assistance of Bi-LSTMs, the system has entrance to more statistics, which assistances the method's setting. One extra LSTM layer is added by Bi-LSTM, which changes the data flow's orientation. That simply implies that in the extra LSTM block, the incoming data flows backwards. The outcomes from the 2-LSTM layers have been then combined employing a numerous methods, comprising mean, sum, concatenation or multiplication. Many benefits come with this kind of design for solving real-world issues.

IV.2 DL MODEL'S PERFORMANCE EVALUATION

In order to assess the energy consumption forecast, the various DL techniques' performance metrics have been looked at. The MSE, MSE, MAE, NMSE, correlation, and RMSE have all been used in this study to assess how well the DL model has worked. To compute prediction errors and assess prediction models, several metrics are used. The MAE, MSE, and RMSE are well-known scale-dependent metrics based on real and squared values.

IV.2.1 MSE

The mean square error (MSE) appears to be measured in statistics. It is a risk function that corresponds to predicted values. It could have never been null since it is arbitrary. It has consistently been employed to evaluate estimate performance in a positive way. MSE appears to be a secondary instant that takes estimate variance and error causes into account. The MSE seems to be an unbiased predictor with estimate directionality. It has been calculated using the mean squared variances between the actual and anticipated values.

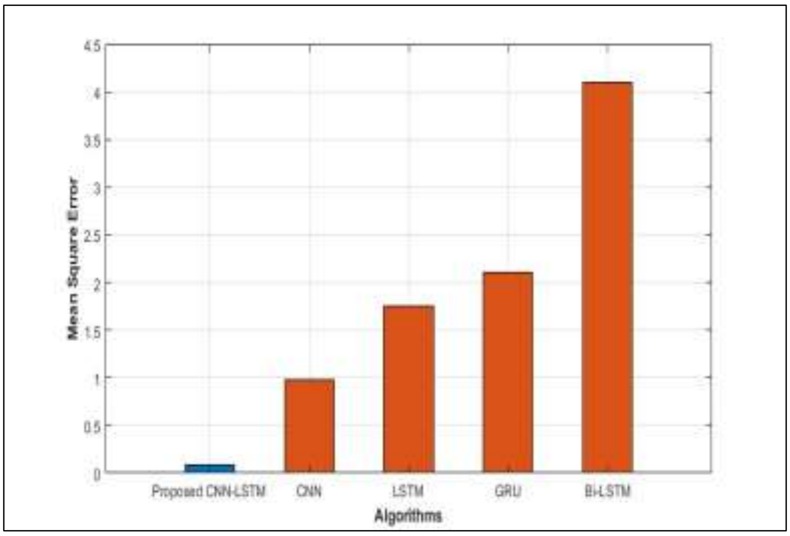

Figure 5: Obtained MSE.
Source: Authors, (2026).

The above Figure 5 indicates the graphical chart of MSE. The result indicated that the presented CNN-LSTM model has attained less MSE of 0.080762 when compared to other method like CNN, Bi-LSTM, GRU, and LSTM. Moreover, the attained MSE of CNN, Bi-LSTM, GRU, and LSTM are 0.979475, 4.10168, 2.099311, and 1.754408, correspondingly. It is evident that the presented method has less prediction error.

IV.2.2 RMSE

The MSE appears to be a statistic that is frequently used in estimates. The RMSE was utilized instead of the MSE by taking the square root. The RMSE calculates how far an estimate deviates from reality. Equation (14) calculates RMSE.

$$\mathrm{RMSE} = \sqrt{1/N \times \sum_{u=1}^{N} (A_u - D_u)^2} \tag{14}$$

Where, $|A_u - D_u|$ is the absolute error, and N is the number of errors.

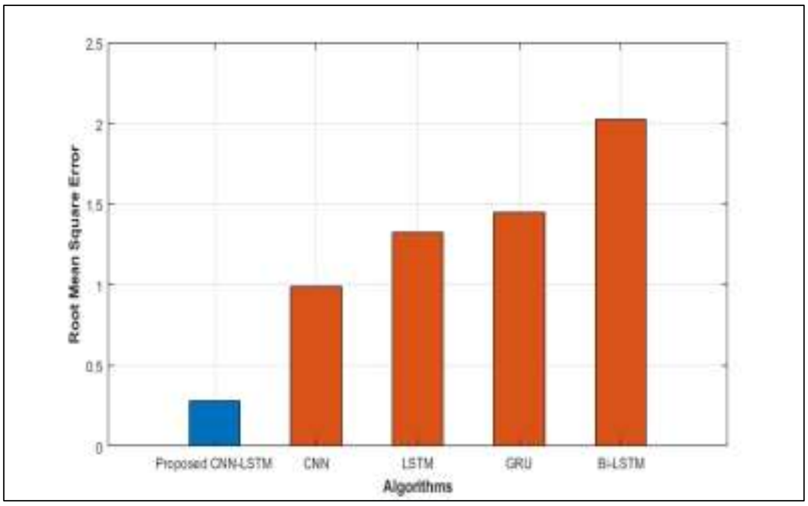

Figure 6: Obtained RMSE.
Source: Authors, (2026).

The above Figure 6 presents the graphical chart of RMSE. The result indicated that the presented CNN-LSTM model has attained less RMSE of 0.284187 when compared to other method like CNN, LSTM, GRU, and Bi-LSTM. Moreover, the attained MSE of CNN, LSTM, GRU, and Bi-LSTM are 0.989, 1.324, 1.448, and 2.025, correspondingly.

IV.2.3 MAE

By considering the average amount of error over a set of predictions while disregarding the direction of the mistake, the MAE assigns less weight to exceptional predictions. Equation (15) calculates MAE.

$$\mathrm{MAE} = \sum_{u=1}^{N} |A_u - D_u| / N \quad (15)$$

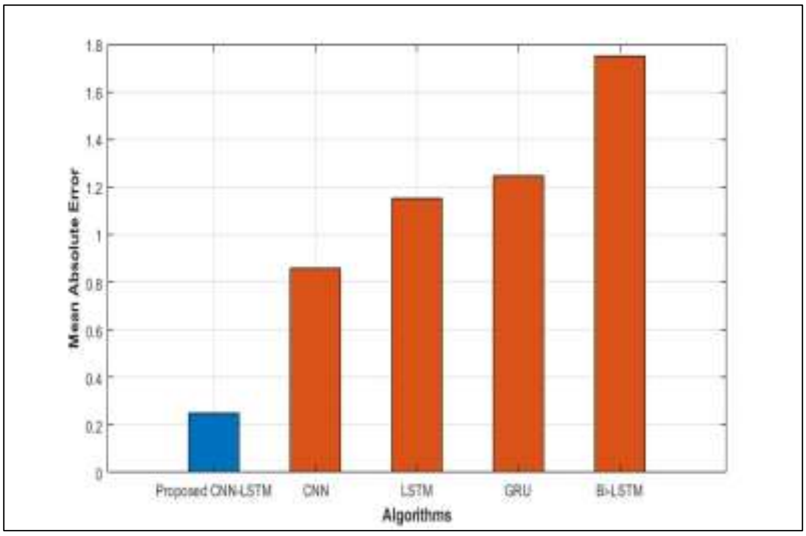

Figure 7: Obtained MAE.
Source: Authors, (2026).

The above Figure 7 present the graphical chart of MAE in which the presented approach has been contrasted with other different method like CNN, Bi-LSTM, GRU and LSTM. From the graph it can be stated that the presented method (CNN-LSTM) has low MAE of 0.251005 and Bi-LSTM has high MAE range. This makes the proposed method more effective.

IV.2.4 NMSE

When the training procedure has been executed for every instance in the training database, one epoch happens. Finding the weights, which reduce a particular total error measure, like the sum of MSE or squared errors, seems to be the ultimate objective. The commonly utilized NMSE is utilized in this study to assess the precision of estimates of energy consumption and is described as follows:

$$\mathrm{NMSE} = 1/_{\sigma^2 N} \times \sum_{u=1}^{N} (A_u - D_u)^2 \quad (16)$$

Where, σ^2 represents the time-series variance.

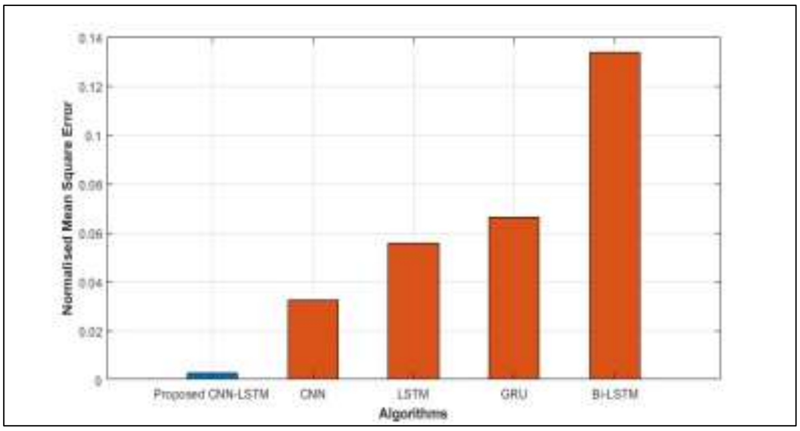

Figure 8: Obtained NMSE.
Source: Authors, (2026).

The above Figure 8 present the graphical chart of NMSE in which the presented model has been contrasted with other different method like CNN, Bi-LSTM, GRU and LSTM. From the graph it can be stated that the presented method (CNN-LSTM) has low NMSE of 0.00272 and Bi-LSTM has high NMSE range. Since the NMSE range is low the performance could be more effective.

IV.2.5 Correlation

The relationship between parameters or attributes in a dataset is quantified by correlation coefficients. There isn't any inclination for the levels of the parameters to rise or fall together when there has been no connection between them. Even if two variables have been uncorrelated, they could still not be autonomous because of a nonlinear connection.

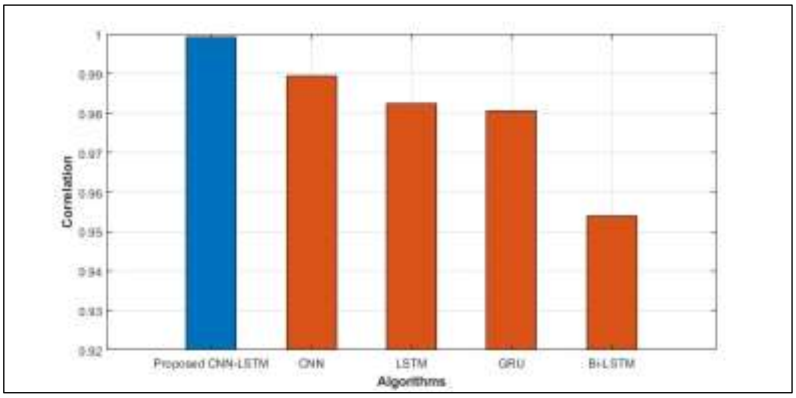

Figure 9: Obtained correlation.
Source: Authors, (2026).

The above Figure 9 present the graphical chart of correlation in which the presented approach was contrasted with other different model like CNN, Bi-LSTM, LSTM and GRU. From the graph it can be stated that the presented method (CNN-LSTM) has high correlation range of 0.999212 and Bi-LSTM has low correlation range about 0.95394. The method with higher correlation is suitable for accurate prediction. Thus, the developed model has higher prediction reliability.

IV.3 PERFORMANCE EVALUATION OF PRESENTED CNN-LSTM

For the prediction of energy consumption, accurate prediction is crucial. Since the results of the obtained prediction have not been very excellent, it would appear that developing a more trustworthy method is essential.

Table 2: Performance of the proposed method CNN-LSTM.

Evaluation metrics	Proposed CNN-LSTM
MAE	0.251005
RMSE	0.284187
MSE	0.080762
NMSE	0.00272
Correlation	0.999212

Source: Authors, (2026).

When evaluating the performance of the proposed technique, the MAE, RMSE, MSE, NMSE, and Correlation were all taken into account. Table 2 and Figure 10 displays the outcomes of these variables used in the study, which made use of 80% training data and 20% testing data.

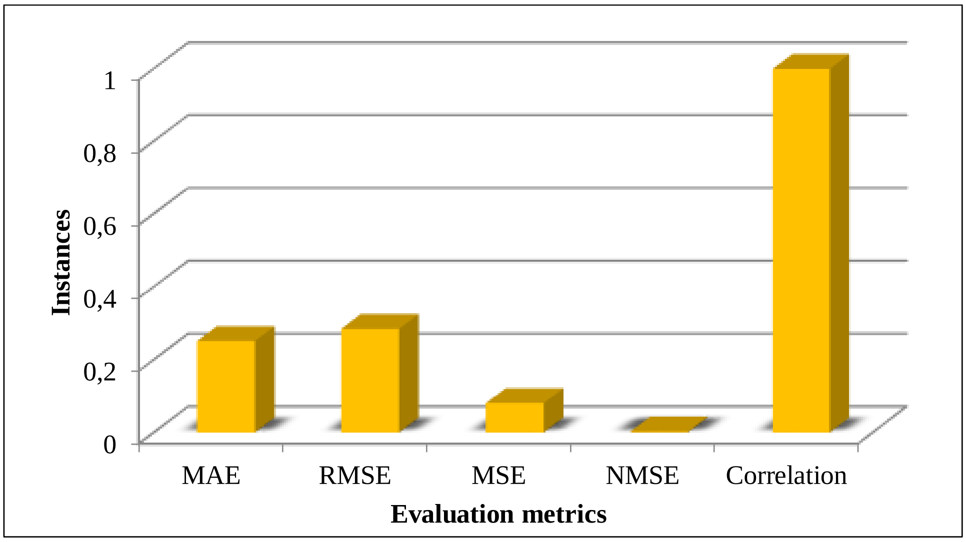

Figure 10: CNN-LSTM model performance.
Source: Authors, (2026).

The MAE, RMSE, MSE, NMSE, and Correlation of the provided CNN-LSTM model are all 0.251005, 0.284187, 0.080762, 0.00272, and 0.999212, respectively. According to the findings, the provided model has achieved less error in the prediction of energy consumption.

IV.4 COMPARISON

To determine the viability of the offered methods, proposed CNN-LSTM models were evaluated and compared to other methods already in use. The RMSE comparisons of current strategy with various approaches are shown in Table 3, and Figure 11. The presented DL model was compared with existing models like Support Vector-Regression (SVR), Gradient-Boosting Regression Tree (GBRT), CNN, and XGBoost [15].

Table 3: Comparison of RMSE.

Method	RMSE
SVR	154.79
GBRT	163.23
CNN	231.96
XGBoost	130.78
Proposed CNN-LSTM	0.284

Source: Authors, (2026).

The result indicated that the presented CNN-LSTM has attained less RMSE of 0.284 when compared to other state-of-art methods. The SVR method has obtained RMSE as 154.79, GBRT model has attained RMSE as 163.23, CNN approach has attained RMSE as 231.96, and XGBoost has attained RMSE as 130.78. From the comparison outcome, it is evident that the presented model's RMSE has enhanced up to 90% than the other existing methods.

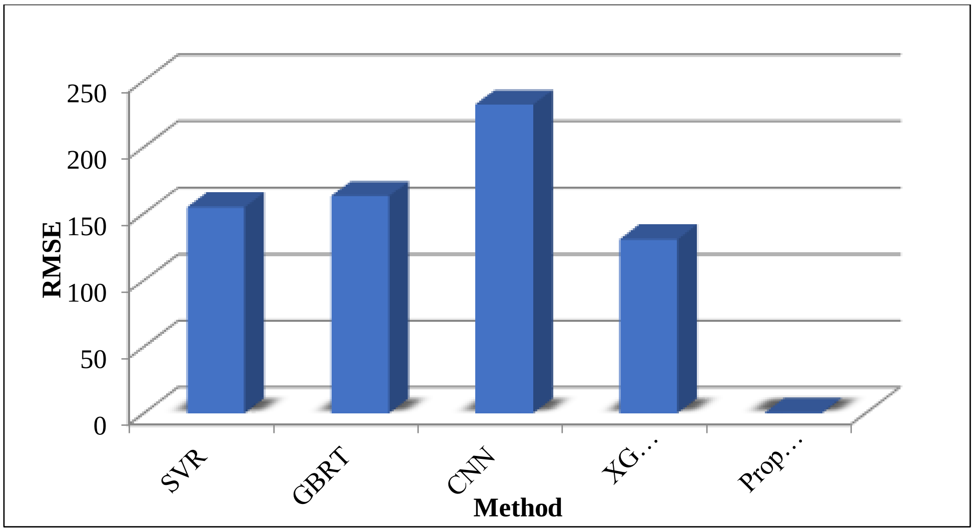

Figure 11: RMSE comparison.
Source: Authors, (2026).

V. CONCLUSIONS

AM seems to be a comprehensive manufacturing method that integrates a number of technologies and is presently used in a wide range of sectors. However, in AM techniques, energy use has grown to be a big problem. As a result, a hybrid DL (CNN-LSTM) strategy is suggested. A study of relevant studies highlighting the importance of CNN and LSTM in the industrial arena served as the inspiration for the suggested strategy. Data related to printing are used as source in a suggested DL-based energy consumption forecasting technique. Moreover, to enlarge the database, data augmentation process has been performed. In addition, pre-processing was performed to remove the duplicate data, missing data imputation, and data normalization. Hereafter, feature extraction was done by PCA that extracts the required features from pre-processed data for prediction. A novel hybrid CNN-LSTM model has been finally implemented for predicting the energy consumption. The result indicated that the presented model has attained less prediction errors while contrasted to other existing and state-of-art methods. Thus, the presented CNN-LSTM model has higher prediction reliability. However, this method employs smaller parameters for predicting 3D printing's energy consumption. Thus, in future variety of data kinds will be used for predicting energy consumption using optimization method with different hybrid DL framework.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: M. Jayakrishna and M. Vijay.
Methodology: M. Jayakrishna and P. Manoj Kumar.
Investigation: M. Jayakrishna and M. Vijay.
Discussion of results: M. Jayakrishna and P. Manoj Kumar.
Writing – Original Draft: M. Jayakrishna and M. Vijay.
Writing – Review and Editing: P. Manoj Kumar and R. Suthan
Resources: M. Jayakrishna and M. Vijay.
Supervision: M. Vijay
Approval of the final text: M. Jayakrishna, M. Vijay, P. Manoj Kumar and R. Suthan.

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