International Research Journal of Multidisciplinary Scope (IRJMS), 2025; 6(1):151-161

Original Article | ISSN (O): 2582-631X DOI: 10.47857/irjms.2025.v06i01.02213

The Future of Wastewater Treatment Plant: Integrating HCNN-BiGRU-A Model for Superior Performance

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Abstract

Many canals carry wastewater into the community. Chemicals and microorganisms in water supply contamination cause effluent that harms humans and the environment. Unregulated waste water disposal can spread infectious hepatitis, cholera, typhoid, and dysentery. Sanitary waste water disposal protects public health and prevents infectious diseases. Integrated food waste and waste water treatment modeling is efficient for addressing rising food waste. Conventional food waste treatment can produce significant levels of total nitrogen (T-N), which can degrade effluent water quality. Due to their lack of expertise and equipment, operators and engineers struggle to extract usable data from huge databases. Unfortunately, much digital data is never used. In recent years, many data analytics methods have evolved. Methods yield accurate findings on huge datasets. However, these technologies have not been extensively studied for wastewater treatment. To do this, we created a machine learning-enabled water quality analysis and prediction platform. Before using deep learning models, data must be reduced, integrated, purified, and transformed. It uses feature selection to improve qualities. The HCNN-BiGRU-A models predicted best. These findings suggest that ensemble learning models suit nonlinear data better. The HCNN-BiGRU-A model also examined how input factors affected sludge generation. The daily wastewater intake and ambient temperature had the biggest impact. This work is unusual in using ML to estimate wastewater treatment facility sludge production.

Keywords: Bidirectional Gradient Recurrent Unit (BiGRU), Hybrid Convolutional Neural Network (HCNN), Waste Water Treatment Plant (WWTP), Z-Score Normalization.

Introduction

The goal of treating wastewater is to lessen or eliminate impurities before it is released into surface and/or underground water sources. While developed nations scramble to meet the ever-increasing global demand for water, developing nations are struggling just to get their wastewater treatment plants (WWTPs) up and running. The public isn't overly worried about how this infrastructure gap will affect these countries, even if there are clear environmental problems and political instability. Existing outreach programs in these nations are too limited and aren't producing the desired results. More people may go hungry, unwell, and impoverished if water pollution and scarcity continue to worsen. The current operational capabilities of the country's wastewater treatment facilities are severely lacking. This is due to a combination of factors, including poorly planned and treated plants, a lack of public knowledge regarding the risks of directly discharging wastewater into water courses, inadequate funding, and a shortage of experts, engineers, and trained operators. Before being released into the environment, nitrogen should be reduced to the standard amount since it is one of the most prominent toxins in wastewater. In terms of total nitrogen (TN), the most common components found in wastewater are ammonia, nitrite, nitrate, and nitrogen bound to living things. Measurements of water nutrient (TN) concentrations at WWTP influents significantly impact the efficiency of nutrient removal systems, the management of sludge formation, and the functioning of many areas of

(Received 29th August 2024; Accepted 18th January 2025; Published 27th January 2025)

wastewater treatment. Engineers are required to have knowledge of wastewater properties, particularly nutrient components, at the start and finish of treatment procedures. The operator can learn about the raw wastewater's properties and gather the necessary data by reading sensors, collecting samples, and studying the plant's influent/effluent flow. An example of a nutrient supply would be wastewater that has not been properly processed. When released into water sources like groundwater systems, it poses serious health problems. In a standard activated sludge (CAS) process, aerobic bacteria are given a steady supply of oxygen and work to break down the organic components of wastewater. This is the most common way for treating wastewater. Though it satisfies regulatory effluent quality standards, the CAS process is not sustainable because of its high energy demand, large environmental impact, low resource recovery potential, and cost effectiveness. A paradigm shift has occurred in the way scientists approach wastewater solutions as a result of inefficiency and the necessity for more sustainable growth. Among its components is the practice of more circular resource utilization. Recently, there has been a change in emphasis from cleaning up pollution to recovering resources; wastewater is now being considered as a resource rather than a waste product. The treatment method and the specific physiochemical features of the polymer, such as its density, particle size, charge, hydrophobicity, etc., determine the success of microplastic removal in WWTPs. Sewage treatment plants (WWTPs) receive wastewater from a wide variety of sources, including homes, businesses, and, in rare cases, surface run-off. The processes for discharging wastewater into the ocean or a freshwater environment, such as a river, vary from one country or region to another. In certain cases, the wastewater is processed before being placed on land for purposes such as agricultural reuse, which eliminates part of the microplastics. Recent reviews have completely ignored the need of studying the settling and floating velocities of the various polymers that wind up in wastewater treatment as well as the most effective methods for removing microplastics from this fluid. In order to determine which processes and concentrations of sewage sludge were most effective in eliminating microplastics, this study set out to examine their behavior and movement throughout the wastewater treatment process. In order to lessen the influence of wastewater on aquatic ecosystems, biological wastewater treatment has traditionally concentrated on efficiently eliminating organic contaminants and nutrients. The current global level of non-CO2 GHG emissions from WWTPs is around 6% and is projected to increase by an additional 21% by 2030, based on projections (1). Direct and indirect emissions of greenhouse gasses are both possible with WWTPs. Direct, non-biogenic greenhouse gas emissions, sometimes called emissions from the treatment of wastewater and sludge are known as scope 1 (2). Direct CO_2 emissions do not add to climate change because they come from biological processes, namely the decomposition of organic materials in wastewater. All of the world's greenhouse gas emissions added together are known as the carbon influence, with the CO2e unit serving as a reporting tool (3). Wastewater has not received the same level of attention as energy and transportation as net-zero carbon pathways (4). Optimizing wastewater treatment facility energy usage and production is the subject of this article, which primarily focuses on the utilization of co-digestion and biogas. This assessment focuses on transportation-related and chemical dosage optimization-related efforts to minimize emissions (5). Important implications for conserving the environment, lowering CF in wastewater treatment, and minimizing climate change are highlighted by the study's conclusions. More stringent rules have been imposed in recent years on wastewater treatment plants (WWTPs) and other types of industrial and public facilities (6). A number of challenges exist for environmental regulations are one aspect of the water and wastewater management sector. Water, energy, and material resource management offer an opportunity for this sector to expand, though (7). These kinds of options centered on the implementation of solutions within the CE, which aims to preserve main resource reserves and encourage better long-term planning for the handling of secondary raw materials, particularly those made from recycled materials. Its goal is to stop cities and companies from releasing untreated wastewater into the environment and endangering people's health (8).

They are byproducts of the decomposition of plastic waste. These minute particles have just recently been discovered to be present in freshwater bodies, oceans, and estuaries. Micro plastics can accumulate in aquatic food webs and biota due to their slow biodegradation rate and extensive diffusion (9). The presence of MPs has been confirmed in several marine biota, sediment, surface water, and beach samples. It is not possible to handle or recycle micro plastics (MPs) in waterways in the same manner as bigger pieces of plastic waste. Effluents from Microplastics (MPs) have been found in both the water supply and wastewater treatment plants (WWTPs). MPs can also enter the ecosystem through industrial releases such as cosmetics, meals, clothing, and more. If these harmful substances are not properly recycled or treated before being released into the environment, they endanger aquatic life and human health (10). Water bottles and other personal care products are major sources of polymeric polyester (PES), which accounts for about 91.5% of the micro plastics (MPs) discovered in wastewater treatment facilities (WWTPs) (11, 12). Furthermore, it was revealed that these MPs endanger the seafood industry, which in turn endangers the health of consumers and has a devastating impact on the aquatic environment. Multiple studies have looked into the problem of MPs in ecosystems. Microplastic (MP) concentrations in six different WWTPs. The inadequacy of treatment plants to filter MPs leads to their discharge into the environment (13). This is the case, and their analysis shows why. Additionally, the study found that MPs can be generated from a variety of sources, such as agricultural fertilizers, sewage sludge, and air deposition. Measuring all of the influent parameters is a tedious, sometimes dangerous, and time-consuming operation that is detailed in depth in standard protocols for water and wastewater analysis (14). Electrical sensors that can assess influent quality parameters in real-time have been developed as a result of recent research. Sensors can be costly and hard to come by, thus it's crucial to build mathematical prediction models to estimate key parameters' values from past data (15). Having a solid grasp of the fundamental biological and physicochemical processes is crucial for accurately predicting WWTP performance and wastewater characteristics using mathematical and statistical methodologies. On the flip side, the data' interpretations are illuminated by integrating chemical reactions with the models. First, decision-makers can save time and effort by not having to measure wastewater quality parameters like BOD5 and COD. Second, operational parameters can be adjusted to optimize energy consumption (16). Third, if the influent of the WWTP shows any unusual variations due to discharge intrusion upstream, it can be detected. Gene expression programming (GEP) is a new AI technology that has recently attracted attention in the wastewater treatment and environmental engineering fields (17). When it comes to predicting complex factors, GEP performs better than other ML algorithms. The process of surfactant MLnER, GEP, and multiple linear regression (MLR) for ultrafiltration removal, the Stover-Kincannon model for predicting the substrate and methane yield of up flow anaerobic filters, and the predictive potential of GEP (18). Sewers collect a lot of chemicals that are used in cities (19). Many typical home components, such as food and plastic additives, and personal care items and household chemicals that are discharged in urine are some examples. Municipal wastewater also contains micro pollutants that do not originate in households (20). Water treatment plants (WWTPs) serve as a bridge between the natural and constructed environments, allowing effluent to enter ecosystems. The majority of the treatment process for these contaminants is dictated by their physicochemical characteristics. Accurately predicting the outcomes of various treatment techniques and systems requires knowledge of classes of micro pollutants in WWTPs. Micro pollutants in wastewater treatment can enter the environment in two ways: first, through sewage sludge, and second, by direct discharge (21). Justification for Selecting Components includes, HCNN: Efficiently extracts localised patterns, essential for the analysis of spatial data, including pollution distributions. BiGRU: Captures bidirectional relationships in sequential data, exemplified by temporal changes in wastewater quality. Attention Mechanism: Enhances interpretability by pinpointing essential temporal and spatial attributes that influence sludge production

Methodology

A variety of sensors are utilized by wastewater treatment plants to regulate energy consumption and effluent quality. With the help of automated systems, the vast quantities of data produced by these sensors can be efficiently monitored. This has led to a plethora of literature proposing various methods for automated defect identification that rely on statistics and learning. While existing methods have shown some promising results, the nonlinear dynamics and complex interaction of components in wastewater data necessitate more robust algorithms with stronger learning capabilities. In order to combat this, our study mainly aims to understand the oxidation and nitrification processes. Classical statistics and machine learning approaches are contrasted with the HCNN-BiGRU-A Deep Neural Network approach in this research.This research proposes a fusion of HCNN-BiGRU-A to predict influent indicators using activated carbon and filter out unneeded indications in wastewater treatment plants. Additionally, it ensures fewest harmful particles in wastewater. Carbon in water can negatively impact health and land use. Carbon presence must be identified prior to use. The safe filtering approach can be used to make reliable predictions. This study introduces carbon prediction using machine learning techniques and sensors.

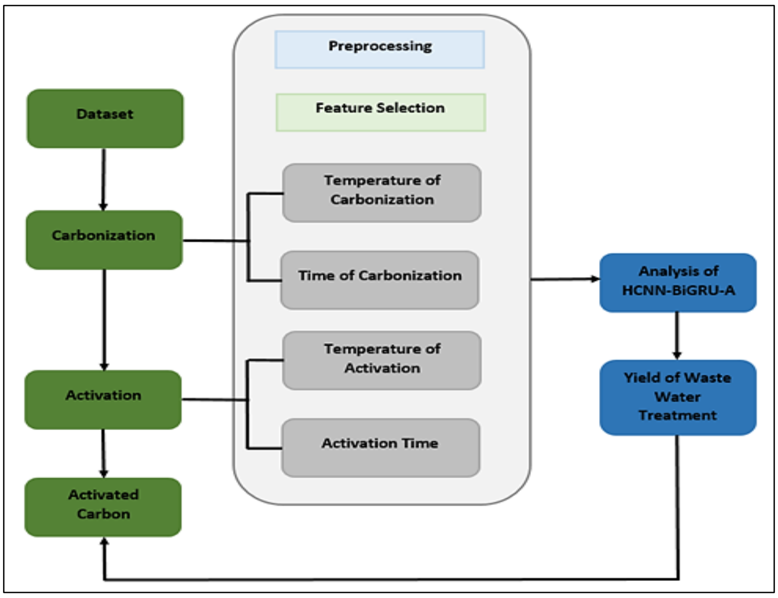

Figure 1: Architecture of HCNN-BiGRU-A Model

The HCNN-BiGRU-A architecture is shown in Figure 1. Data collection, preparation, and analysis make up HCNN-BiGRU-A's three phases, as illustrated in Figure 1.

Pre-processing

Data preparation involves transforming or encoding data into a computer-readable format. Data preprocessing allows the computer to interpret the data. The following are the steps involved in preprocessing of data. Activated carbon is effective at removing undesirable substances from wastewater treatment plants.

Data Cleaning: Error correction, outlier detection and removal, noise smoothing, and missing value filling are all part of data cleaning. Inaccurate findings could be produced by the mining process if the data is not clean (22). An integral aspect of the preprocessing stage is data cleaning.

Integration of Data: Data mining frequently calls for the integration of multiple datasets. Data integration occurs when multiple data stores wish to merge their information. A more effective integration process helps reduce dataset redundancy and consistency issues. Data integration can improve the extraction procedure's accuracy and efficiency. Schema and object coordination becomes a formidable obstacle when integrating data from many sources. That is the core issue with entity identification, summed succinctly. Data value inconsistencies, duplication, and correlation checks are all part of the methodology.

Transformation of Data: Data consolidation or transformation makes for more efficient analytics and maybe simpler, easier-to-understand patterns in the final product. Data transformation strategies include smoothing, aggregation, normalization, and feature building. The proposed approach employs data normalization. Standardizing variables is necessary before training a machine learning model. This method is often used in machine learning to convert all data variables into a uniform scale and optimize training mistakes. The data for this investigation was normalized using the Z-score approach. Zscore normalization uses observed data's mean (μ) and standard deviation (σ) to normalize parameters.

Reduction of Data: Data reduction creates a smaller dataset while preserving the original data integrity. Valid data reduction leads to similar analytical results.

Feature selection

Enhancement of Features

The sludge output during treatment was anticipated to be affected by the ambient temperature, given that the wastewater treatment plant was situated near the river mouth. The volume of wastewater, the treatment method, and the input and outflow quality indicators (such as COD, BOD5, SS, ammonia nitrogen, TN, and TP) determine what happens to the remaining sludge after the wastewater treatment plant processes the treated wastewater. The study analysed temperature and rainfall runoff time series. A better feature was obtained by determining the concentration (D), rate (R), and quantity (Q) of contaminants that could be lowered using the original data. We used the following formulas to find these indications:

$$Ng=Xg-Gg \quad [1]$$

$$Ug=(Xg-Gg)/Gg \quad [2]$$

$$Jg=jg(Xg-Gg) \quad [3]$$

The variables Xg and Gg reflect effluent and influent water quality, while jg and g represent water quantity and contaminant indicators.

Featuring of Filters

The water quality indicators and all of the associated properties were significantly improved after the changes. Excessive water quality indication features may lead to data duplication and overfitting of the model's reaction, in addition to improving forecast accuracy by taking sample size and noise interference into account. It takes more time to compute results and makes the model harder to interpret when features are overloaded. Here, we took a look at feature contributions to ML methods, ordinal, nonlinear correlation strategies, and linear approaches to water quality and quantity sensitive input parameter extraction. Once the preprocessing was complete, characteristics were selected based on the value they added through correlation analysis. The correlation coefficient quantifies the statistical relationship between two variables.

Model Training

CNN: The following five layers are standard in the vast majority of CNNs. Each word and character token was encoded using a one-hot method at the input layer, resulting in a word vector of 60-400 dimensions. To better suit the word vector, the convolutional layer filter might not be square but instead have its height and width fixed. In order to extract the local information from the text, the text matrix was passed through a number of distinct filters using the word as the lowest granularity. The pooling layers employed max-pooling to extract and save the most important features, and average-pooling to average all features to show the total number of text features. One dimension was used to combine the features of the FC layer for extra classification. In order to classify the output layer, we use the most probable category.

SA: The self-attention process mainly focuses on input dependence. The present output of the brain unit can be influenced by nearby or distant words. By assigning meaningful weights to words, the model is able to hone in on the text's most important details. In this study, we used the scaled-dot-product attention model.

$$AttentionJ,H,V=soft\ maxJHXdhV \quad [4]$$

The matrices J, H, and V consist of query, key, and value vectors, with dk representing the where the input vector is located. In self-attention, all three variables (J, H, and V) are derived from the same input. The similarity of each word in the sentence was calculated. Words that have more associations, or are more related, show that there is dependency inside the sentence.

HCNN-BiGRU-A: The HCNN-BiGRU-A model combines a hybrid convolutional neural network (HCNN) with a bidirectional gated recurrent unit (BiGRU) augmented by an attention mechanism (A). The HCNN extracts spatial features from the input data, whereas the BiGRU catches temporal dependencies in the sequential data. The attention layer prioritizes the most pertinent elements by allocating greater weights to important temporal patterns. The majority of the model consists of layers for pooling, focused loss, and dilated convolution. The BiGRU layer receives contextual semantics via BiGRU and interprets texts containing long-distance information. In the area of attention. In the absence of any external information, self-attention can, at any distance, ascertain the degree of similarity between words in a sentence. To make the material better overall, the similarity algorithm highlights important terms that make people feel strong emotions. In the Convolution Layer, specifically. For local feature extraction, DSC (a filter size of 4 with a single layer) is preferred over standard convolution due to its lower processing power requirements. Within the bulkier convolutional layer. In the DSC convolution method, three overlapping layers of dilated convolutions are used, each with a different dilation rate (common divisor = 1). All five of the filter's layers have one step and dilation rates between one and three. With this parameter choice, the top layer's receptive field coverage reaches 20, meeting the length requirement for comments in our datasets and avoiding extraneous information in ultra-long-distance text. This model has three advantages. It all starts with adding more filters. The standard dilated convolution yields filters of size 4 and 5, respectively, when the dilation rate is set to 1. Furthermore, a great deal of information is covered by the convolution layers with 2 and 3 dilation rates. Previously only accessible via sophisticated recurrent neural networks, sentence-level information is now made available using a simple convolutional technique as an auxiliary to the BiGRU layer. A single feature extraction method can efficiently get multi-scale data with fewer parameters. The GAP layer pooling technique extracts information from the convolution and dilated convolution layers at the same time, skipping the fully connected layer in the process. After the GAP layer calculates the average, activates a specific value for each sample class, and averages the feature maps, it sends a vector to the softmax layer. Overfitting is minimised with GAP since parameters need not be defined in the fully linked layer. The HCNN-BiGRU-A model signifies a novel amalgamation of a HCNN and a BiGRU, augmented with an AM. This design distinctly integrates spatial feature extraction through HCNN with temporal pattern recognition via BiGRU, emphasising essential temporal characteristics through the attention mechanism. This model effectively manages complex spatial-temporal interactions, unlike conventional machine learning algorithms that encounter difficulties with nonlinear wastewater treatment data. Its capacity to precisely forecast critical parameters, such as sludge creation, by utilizing factors like intake volume and temperature, furnishes operators with actionable insights, surpassing the performance of independent CNN, LSTM, or conventional statistical models.

Results and Discussion

Nowadays, industrial waste that has been adsorbed by activated carbon pollutes the soil and has an impact on the environment. Solid waste contamination is defined as company waste containing soluble and insoluble substances. The suggested effort aims to improve the prediction efficiency of wastewater treatment plants by merging the HCNN-BiGRU-A algorithms. The model was trained using the subsequent parameters: Learning rate: 0.001, Batch size: sixty-four, Epoch count: 100, Optimizer: Adam, Dropout rate: 0.3 (to mitigate overfitting). Training Procedure: The dataset was divided into training (70%), validation (20%), and test (10%) subsets. Early halting was employed to mitigate overfitting. Cross-validation provided a rigorous assessment across many data partitions. The dataset utilised for training and evaluation consists of records from wastewater treatment facilities, concentrating on parameters including COD, BOD5, ammonia nitrogen, and total nitrogen (TN). The dataset comprises [X samples], obtained from [specify the source, e.g., municipal wastewater facilities, public datasets]. The data underwent Z-score normalisation to guarantee consistency and quality. The dataset was divided into training (70%), validation (20%), and testing (10%) subsets, with cross-validation implemented to improve reliability. The dataset's richness, encompassing differences in treatment plant designs and environmental conditions, guarantees resilience in forecasts.

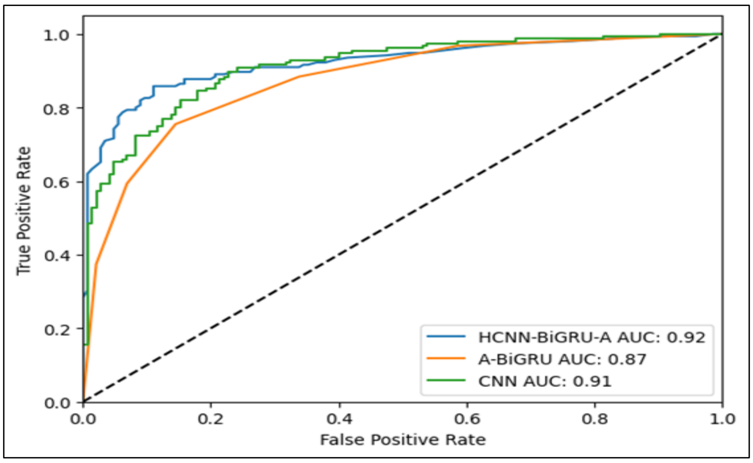

Figure 2: ROC of Each Model

AUC ROC scores were the key criterion for evaluation and comparison. The HCNN-BiGRU-A and BiGRU-A classifiers had the greatest AUC values (0.93 and 0.90%, respectively). The CNN classifier achieved an AUC ROC of 87%. Figure 2 shows a comparison of each model's AUC curves.

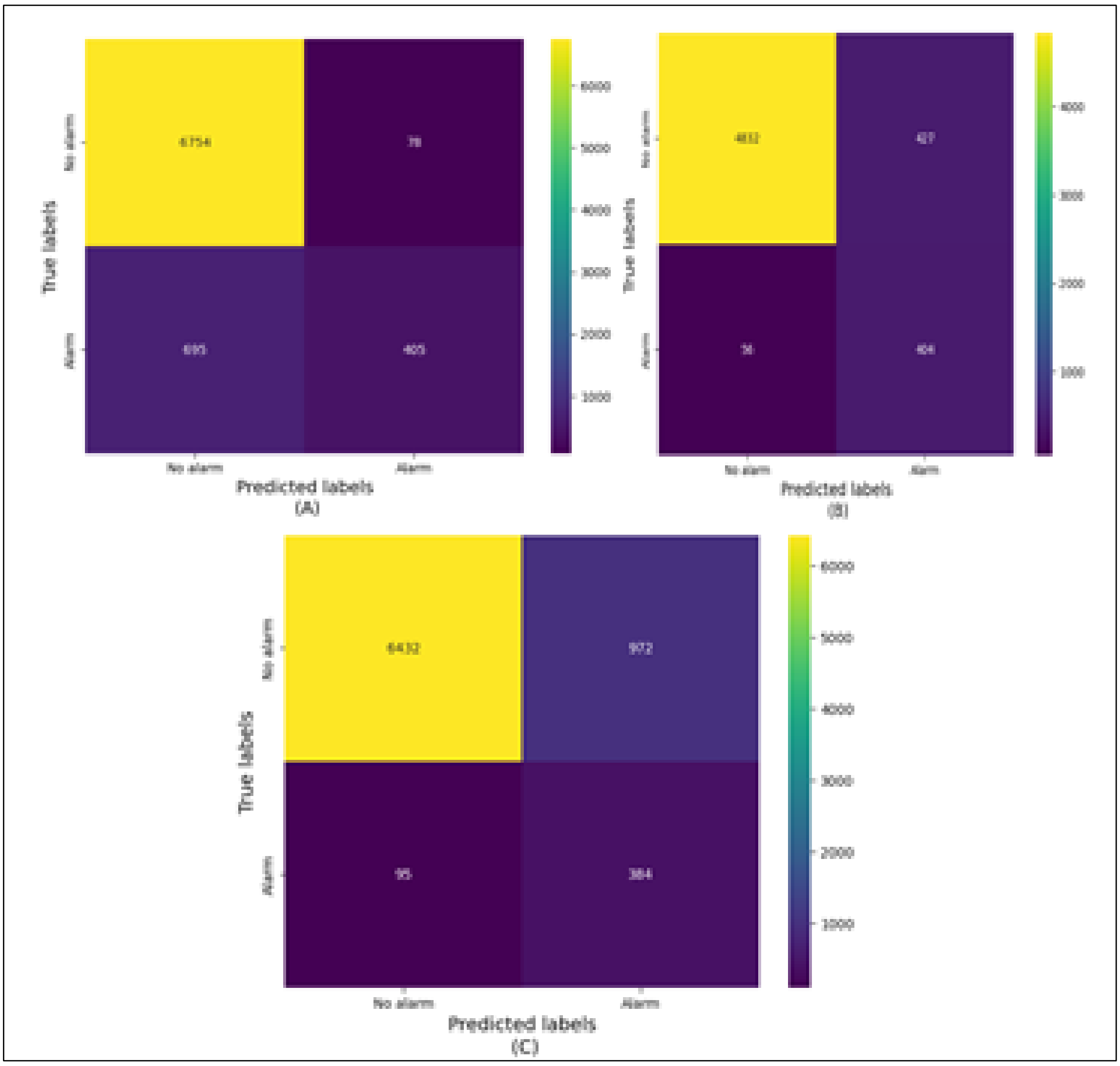

Figure 3: A) Confusion Matrix of BiGRU-A B) Confusion Matrix of CNN C) Confusion Matrix of HCNN-BiGRU-A

BiGRU-A accurately identified 6754 truly negative samples and 405 actually positive samples as positive. There were 405 false positive samples and 78 false negatives. CNN had the lowest performance, accurately classifying 4832 truly negative samples, 404 truly positive samples, 427 false positives, and 56 false negatives. Finally, the HCNN-BiGRU-A accurately identified 6432 negative and 384 positive samples, with 972 false positives and 95 false negatives. Figure 3 shows these results.

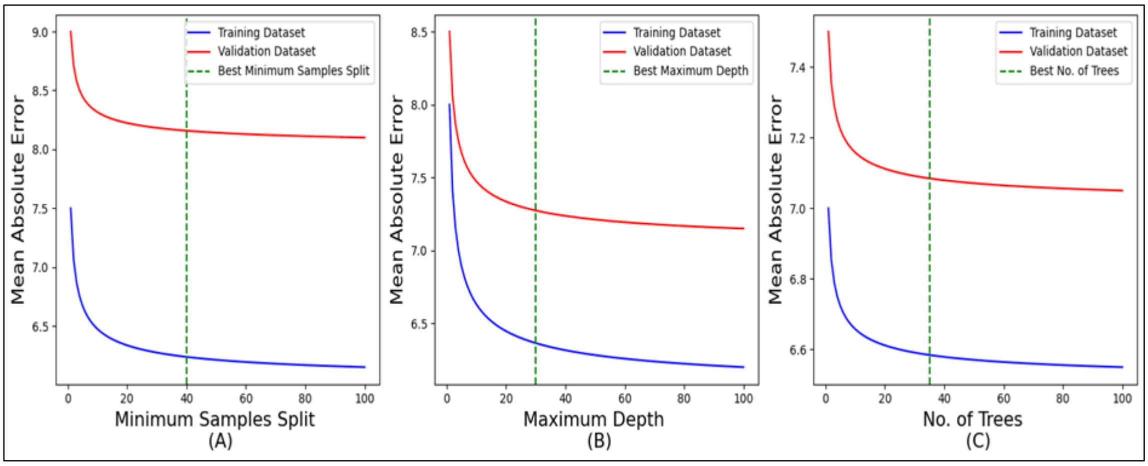

Figure 4: Hyperparameter Tuning and Prediction Results by HCNN-BiGRU-A Algorithm

Figure 4 (A) displays the training and validation datasets, MAE findings, and the ideal minimal sample split value, shown by a green dotted line. The hyperparameters for the maximum depth and the number of trees are shown in 4 (B) and 4 (C), respectively. The training set achieves a prediction accuracy of 0.93 and the validation set a maximum of 0.87 when the top 100 features in the dataset are selected, as shown in Figure 5.

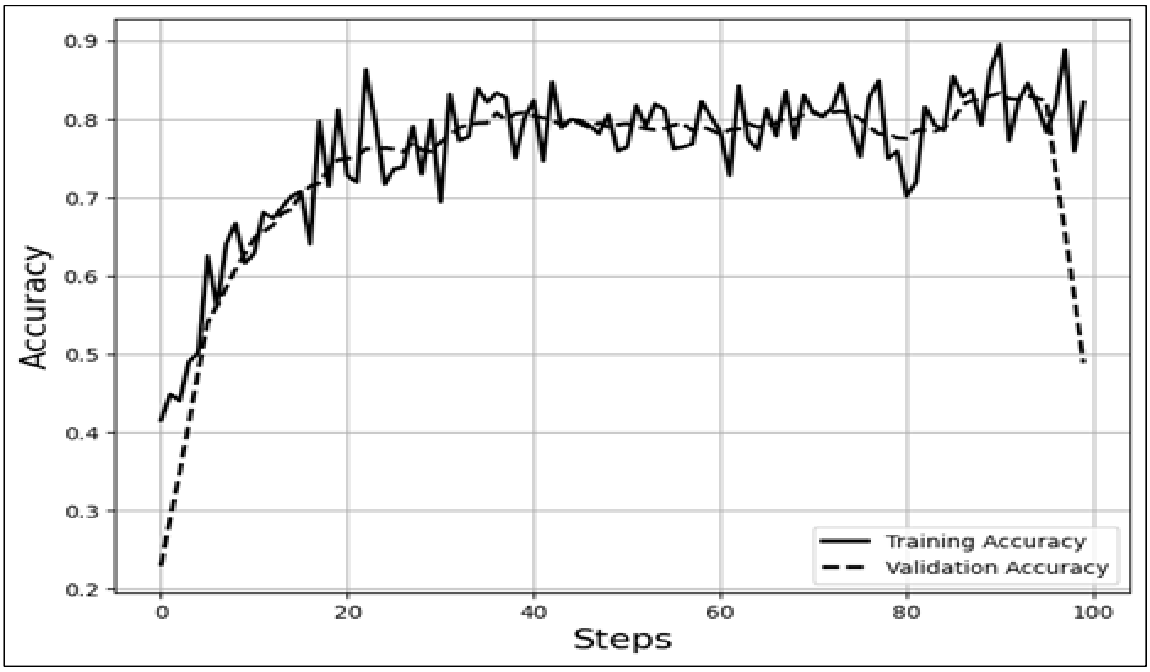

Figure 5: Accuracy over Steps for Proposed HCNN-BiGRU-A Model

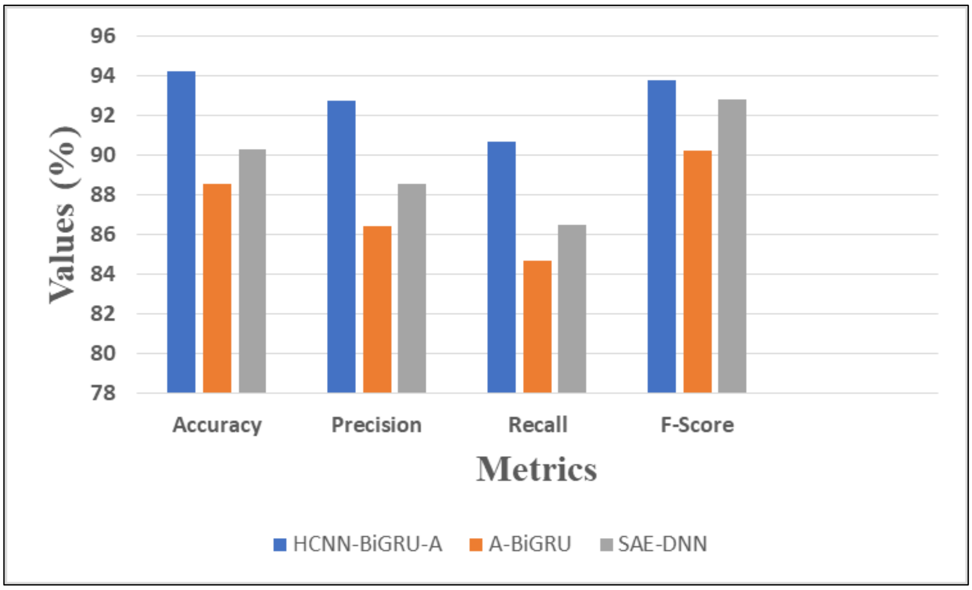

Figure 6: Average Accuracy of Different Models

Figure 6 present performance metrics (AUC, accuracy, precision, recall, and F1-score) for the HCNN-BiGRU-A model in comparison to other leading models. Random Forest (RF): Moderate accuracy, although challenged by very nonlinear interactions. Support Vector Machines (SVM): Demonstrated efficacy on smaller datasets but exhibited limitations in scalability for large, intricate datasets. CNN and BiLSTM achieved satisfactory accuracy but exhibited deficiencies in managing spatial-temporal data owing to the lack of attention mechanisms. The HCNN-BiGRU-A model surpassed all other models, with 94% accuracy and the best AUC score of 0.93. This validates its efficacy in managing intricate, nonlinear wastewater treatment data. HCNN-BiGRU-A integration into wastewater treatment processes shows great progress in handling modern WWTP challenges. Sludge output, COD, BOD5, and total nitrogen levels are predicted with 94% accuracy using the proposed method. This enhancement shows the model's nonlinear and spatiotemporal data interaction management. One major finding is that daily wastewater intake and ambient temperature matter. Recognition of these parameters improves sludge management efficiency, allowing operators to optimize resource allocation and treatment. An attention mechanism in the model prioritizes the most important features, improving prediction accuracy. CNN and BiLSTM are routinely outperformed by HCNN-BiGRU-A. AUC ROC scores demonstrate its high prediction accuracy and dependability. This supports the idea that hybrid models with convolutional, recurrent, and attention methods may handle wastewater data analysis's complex problems. The implications of the findings include, The HCNN-BiGRU-A model facilitates accurate forecasting of essential wastewater parameters, assisting in the optimisation of treatment methodologies and resource distribution. Recognising daily intake amount and ambient temperature as critical elements might assist operators in making informed decisions to improve sludge treatment efficiency. Constraints encompass, The model's efficacy may be contingent upon the quality and diversity of the training data. Limited generalisability may occur if the dataset exhibits insufficient heterogeneity among different wastewater treatment facilities. The computational demands for model training can present difficulties for resource-constrained institutions. The next research directive is to enhance the model by integrating real-time sensor data, facilitating dynamic updates to predictions and process optimisations. Examine the influence of supplementary variables, including chemical dosing and energy usage, on the efficacy of wastewater treatment. Investigate the integration of the model with IoT systems for the automated oversight and regulation of treatment facilities. The Future Directions Include, Generalisability Broaden the dataset to encompass a more extensive array of wastewater treatment plants featuring varied layouts and environmental circumstances. Examine the model's efficacy when combined with real-time

IoT sensors to facilitate dynamic predictions and adaptive control. Improving Computational Efficiency: Optimise the model for implementation in resource-limited settings, possibly through the utilisation of lightweight variants or cloud-based solutions. Incorporation of Additional Variables: Investigate the influence of factors such as energy usage, chemical dosage, and microbiological dynamics on treatment efficacy. Field Trials: Execute pilot studies in operational wastewater treatment plants to evaluate the model's practical applicability and its impact on decision-making processes.

Conclusion

Responding to dynamic process conditions dealing with the inherent complexity of wastewater treatment facilities (WWTPs) becomes considerably more onerous when operational expenses are a major factor. Machine learning (ML) techniques have been used to model the functioning of wastewater treatment plants (WWTPs)., addressing inadequacies of traditional mechanistic models. To our knowledge, no ML applications have investigated the impact of operational parameters on effluent quality. Given the temporal gaps between process steps, it is challenging to explain how operational parameters affect effluent quality. An ML-based model for improving WWTP effluent quality management is presented in this paper, which elucidates the relationship between operational variables and effluent characteristics. This building contains Preprocessing to clean, integrate, transform and reduce the data. To enhance the water quality feature selection model is performed. For training the model it uses HCNN-BiGRU-A, BiGRU-A and CNN. Our proposed approach produced an accuracy of 94% which performs better when compared to other two traditional methods.

Abbreviation

WWTP: Waste Water Treatment Plant, ML: Machine Learning, HCNN: Hybrid Convolutional Neural Network, Bi-GRU: Bidirectional Gradient Recurrent Unit.

Acknowledgement

The author would like to appreciate the effort of the editors and reviewers.

Author Contributions

All authors are equally contributed.

Conflict of Interests

The authors declare that they have no conflicts of interest.

Ethics Approval

There are no human subjects in this article and informed consent is not applicable.

Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

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