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Research Article

Recent Advancements in Deep Learning Frameworks for Precision Fish Farming Opportunities, Challenges, and Applications

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The growth of the fish is influenced by a variety of scientific factors. So, profit can be easily achieved by using some clever techniques, for example, maintaining the correct pH level along with the dissolved oxygen (DO) level and temperature, as well as turbidity for good growth of fish. Fully grown fish are generally sold at a good price because price of fish in the market is governed by weight as well as size of nurtured fish. Artificial intelligence (AI)-based systems may be created to regulate key water quality factors including salinity, dissolved oxygen, pH, and temperature. The software programme operates on an application server and is connected to multiparameter water quality meters in this system. This study examines smart fish farming methods that show how complicated science and technology may be simplified for use in seafood production. This research focuses on the use of artificial intelligence in fish culture in this setting. The technical specifics of DL approaches used in smart fish farming which includes data and algorithms as well as performance was also examined. In a nutshell, our goal is to provide academics and practitioners with a better understanding of the current state of the art in DL implementation in aquaculture, which will help them deploy smart fish farming applications as well their benefits.

1. Introduction

Growing food in marine waters of coastal as well as in the open ocean has been possible only due to the innovation technology which successfully fulfills the growing demand for seafood [1]. Aquaculture will be the primary method of producing food from our aquatic environment in the future. Aquaculture has an effect on biodiversity since it uses resources such as land (or space), water, seed, and nutrition to produce goods valued by society while also emitting greenhouse gases, waste from uneaten food, faeces, urine, chemotherapy drugs, microorganisms, parasites, and feral animals into in the environment [2, 3]. The addition of eutrophicating agents, poisonous chemicals, infections, illnesses, and worms into wild populations of stock, as well as foreign and genetic material into the ecosystem, can all have severe impacts. However, indirect detrimental consequences such as loss of habitat, niche space alterations, and food web disturbances might occur [4, 5]. Aquaculture is a technique for producing food and other commercial items while also reinstating territory and replenishing barren stocks, as well as repopulating threatened along with endangered animals [6]. Aquaculture has been classified into two categories: marine and freshwater aquaculture. Most NOAA's activities have been focused on the marine aquaculture or raising the aquatic as well as estuarine creatures [7]. Marine aquaculture creates new international trade opportunities while also maintaining resilient functioning waterfronts and coastal cities. In 2018, aquaculture contributed 46.0 percent of the world's fish production, up from 25.7 percent in 2000, and it contributed 29.7% of the world's fish production outside of China, up from 12.7 percent in 2000 [8]. By 2030, 62 percent of food fish will come from aquaculture, with tilapia, carp, and goldfish likely to experience the highest supply growth. Between 2010 and 2030, the world's tilapia production is anticipated to nearly double, from 4.3 million tonnes to 7.3 million tonnes annually. Since aquaculture has developed to supplement our wild fisheries, current and former fishermen are using it to supplement and sustain their fishing careers [9, 10]. Due to farmed seafood products accounting for half of the world's supply of seafood, the United States will have a $16.9 billion seafood deficit in 2020. Marine aquaculture, in addition to and in support of our wild fisheries, provides a domestic source of economically and ecologically viable seafood [11, 12]. Future food production from our watery environment will primarily rely on aquaculture. Aquaculture is a method for generating food and other goods for sale while simultaneously reclaiming land, restoring depleted stocks, and repopulating threatened and endangered species of animals. Marine aquaculture maintains resilient and functional waterfronts and coastal cities while simultaneously generating new prospects for international trade. In addition to and in support of our wild fisheries, marine aquaculture offers a domestic source of economically and environmentally sound seafood. Aquaculture was determined to be more diversified when compared to other agricultural enterprises than other agricultural sectors.

Marine aquaculture practices have been implemented in the United States to produce oysters along with clams, mussels, shrimp, and seaweeds, as well as fish such as coral, black sea low-voiced, sablefish, *Seriola dorsalis*, and pompano to name a few [13]. The much more desirable fish are frequently sold to raise money for other more reasonably priced food items. Thus, both fishing and aquaculture contribute to securing wholesome food for coastline and rural inhabitants and reducing their poverty. While aquaculture is a study that encompasses all aspects of marine life, fisheries only deal with the capture of wild fish or the breeding and harvesting of fish. Unlike aquaculture, which can be either mariculture or a sort of integrated and mixed fish farming, fisheries can be either saltwater or freshwater or wild or cultivated. Humans benefit from aquaculture because it produces a big number of high-quality proteins. In recent decades, aquaculture has become the most rapidly expanding agricultural sector. The production of aquaculture was able to surpass the production wild fisheries in 2013. The abrupt growth in aquaculture has been possible due to the application of research along with the evolution of new technology over the last 50 years. Aquaculture is more diverse than other agriculture sectors when considered the species, food, mass-production processes, illnesses, goods, corporate sectors, and presentation. Almost every area of aquaculture has benefited from scientific and technological perfections. The application of research and the introduction of new technology have supported the rapid expansion of aquaculture in the last 50 years. In terms of species, food, manufacturing processes, sicknesses, products, and corporate and marketing sectors, aquaculture is found to be more diverse when compared with other agricultural businesses. Scientific and technological improvements have benefitted nearly every aspect of aquaculture. A greater feed conversion rate (FCR) along with the reduced feed cost came from better feed formulations derived from nutritional demands of individual species of fish [14]. Disease outbreaks in aquaculture have been minimized because of disease management technology. Even though these and other early discoveries contributed to aquaculture's astonishing expansion, servicing the world's ever-increasing seafood demand remains a formidable task. More aquaculture products are required [15].

Photosynthesis, which creates oxygen, occurs when sunlight strikes aquatic plants during the day. At night, oxygen levels fall due to the respiration of vegetation, animals, and notably fish. Low DO levels induce oxygen depletion, which can lead to fish mortality [16, 17]. A DO concentration of 5 mg/L is recommended for the healthiest fish. Even though the vulnerability of different species to low dissolved oxygen levels varies, most fish species get disturbed when DO falls under 2–4 mg/L [18, 19]. Dissolved oxygen (DO) is majorly used and widely accepted common indicator of water quality (WQ) that is used to detect pollution of rivers. Low DO is thought to be the most adversely damaged water quality because it can immediately reveal the state of aquatic ecosystems. DO sensors are frequently pricey and have a short life span. The quality of farmed water frequently limits the development of aquatic animals in freshwater ponds. As a result, keeping WQ factors within optimal limits while adhering to industrial norms is an important element of aquaculture cultivation. In numerous ways, WQ has an influence on the expansion and survival of pond livestock. Salinity levels that exceed the levels of tolerance for many kinds and species of livestock, for example, might negatively impact their physiology, resulting in decreased survival as well as growth. Lower DO levels in the water results in stress in the livestock which can result in a variety of illnesses. Anoxia and hypoxia can also cause the death of aquatic cattle. The metabolic and immunological systems of livestock are both harmed by high water temperatures. WQ has several effects on growth and survivability of cattle in ponds. Recent developments in AI have impacted various domains of social life and business including farming, tourism, banking, manufacturing, and healthcare industries [20, 21]. The development of AI, cloud computing, and wireless sensors has made the work easier in several domains. The aquaculture domain also gets benefited by the integration of AI, DL, and ML techniques [22, 23].

Automation as well as intelligent technology has aided in the steady growth of aquaculture but in a much more strenuous and cognitive orientation throughout the world, along with the breeding environment which has been gradually shifted to a more viable aquaculture system, considerably improving aquaculture efficiency. Artificial intelligence, machine learning using online data, and low-cost computing have all been important components of a smart decision system. Aquaculture has been improved by incorporating current technology of information, namely, the IoT, big data, or health data, and AI along with cloud services are to name a few, in order to realize an autonomous fishing production [24]. The current study examines machine learning techniques and their applications in aquaculture throughout the previous five years. The current study shows the flaws and issues with machine and deep learning in the aquaculture area, as well as future developments. Numerous scientific variables affect the fish's growth. Profit can thus be simply attained by using some astute methods. Fish that are fully grown are typically sold for a fair price because market fish prices are determined by the weight and size of the raised fish. Systems based on artificial intelligence (AI) may be developed to control important water quality variables. This study looks at clever fish farming techniques that demonstrate how complex science and technology may be made simple for use in the production of seafood. The use of artificial intelligence in fish culture in this environment is the main topic of this study.

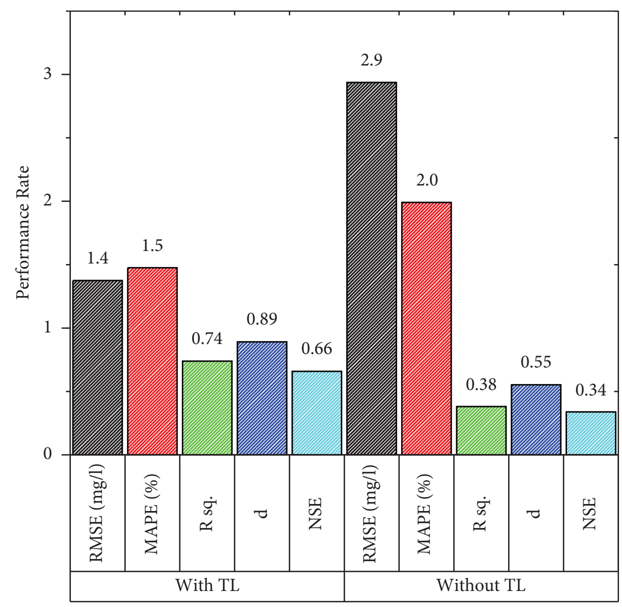

Figure 1: Comparative performance of the various models with and without considering the transfer leaning techniques.

2. State-of-Art Review

The ability to predict the pattern of biochemical oxygen demand (BOD) concentrations is critical for watery area sustainability and green monitoring. The huge amount of experimental data required to construct a reliable DO prognosis model of the system's aquatic environment frequently limits the ability to do so. For the first time, machine learning algorithms and transfer learning approaches were used to collect data from a wide number of aquatic systems to anticipate DO concentration changes in a different (targeted) system. Based on the big dataset, a pretrained DO forecasting model has been developed that included deep learning methods including Attention and ResNet as well as BiLSTM. The pretraining framework's information has been used to construct a DO predictor for specific systems with significantly lower data amount. Some machine learning algorithms are used to assess the models' activity, such as the square error mean definite ratio inaccuracy, coefficient of purpose, and index of agreement, as well as Nash–Sutcliffe efficiency constants. DO concentration prediction necessitates the modelling of a multiple variable temporal series with several linked factors along with a long-time range. As a result, various high-dimensional, nonlinear models capable of modelling and predicting DO concentration patterns could be applied.

To anticipate DO of Delaware River near Trenton, USA, three machine learning methods were used: the radiated-based function (RBF) along with linear genomic programming (known as LGP), multilinear perceptron (MLP), and the support vector machine (SVM), with the SVM model producing the best results. An evolved fuzzy neural network (EFuNN) has been able to show some confidence for forecasting DO with the hourly rate in a time span stretching over a year for a river environment. Back propagation neural networks (BPNNs), the adaptive neural-based fuzzy inference system (ANFIS), and multilinear regression have been used for estimating the DO content in the Feitsui Reservoir located in northern Taiwan.

Aside from artificial neural networks (ANNs), fuzzy logic, and neural fuzzy models, linear genetic programming (LGP) is a newer technique for forecasting DO. An experiment by taking different water from the different lakes Y and Z has been performed.

Figure 1 displays the RMSE, MAPE, R^2, and d, as well as NSE values of the present framework in the absence of transfer learning for lake Y test data. Performance measures were lower in the model with transfer leaning than in the one without (Figure 1). The RMSE and MAPE values both have been increased by the margin of 1.01 mgL−1 and 0.512 percent, respectively, shown that large errors are observed at intemporal data points. R^2, d, and NSE all had their values lowered by 0.29, 0.33, and 0.31 points individually. Furthermore, the R^2, d, and NSE have observed lower values in the absence of transfer learning which concluded that overall framework shows poor performance. Deep learning and transfer learning techniques were used in the abyss of DO concentration temporal series of the aquatic system in this study. Transfer learning (TL) improved model performance in a measurable way. The TL technique provides accurate DO forecast of lake Y while managing more than a year of data collection time [25]. Deep learning (DL) technology has quickly gained popularity and is now being successfully applied in a number of industries, including aquaculture. For information and data processing in smart fish farming, DL generates both new opportunities and a number of obstacles. A new scientific subject known as "smart fish farming" aims to maximise resource efficiency and advance aquacultural growth by tightly combining the Internet of Things (IoT), big data, cloud computing, artificial intelligence, and other contemporary information technologies. Aquaculture is the practice of raising marine animals or plants for the purpose of food production. Fishes, invertebrates, crustaceans, and plants are bred, nurtured, and harvested in both freshwater and saltwater habitats. China and other Asian countries continue to control world manufacturing, which began some 4,000 years ago. Some of the world's poorest communities, as well as major enterprises, collect food through aquaculture [26]. Aquaculture today provides 50% of seafood consumed by humans on a global scale, a figure that is increasing with the growing world population. Food and Agriculture Organization (FAO) claims that fish categorization is the process of identifying fish breeds based on physiognomies as well as similarities. It is also referred to as a way of identifying fish species. Computerized fish cataloging, on the other hand, can improve the accuracy of fish species categorization and identification while speeding up the process [27]. This work also contains several strategies for automated fish species identification. In this work, various machine learning models have been used such as J48, random forest (RF), KNN, and CART to do classification. Traditional rule-based algorithms are not able to provide any forecasting characteristic for the unidentified datasets; hence, classification has been utilized for that purpose. CNN is a type of deep learning model with a higher computational complexity than machine learning. Only machine learning algorithms were considered in this work because of their lower computational complexity. In comparison to the standard machine learning models, CNN requires a lot of training time. DL is a branch of machine learning that enhances data processing by autonomously identifying extremely complicated and dynamic features through layers and sequences rather than manually designing the best feature representations for a given type of data based on domain expertise [28]. DL offers sophisticated analytical tools for uncovering, measuring, and comprehending the massive amounts of information in big data to assist smart fish farming. These tools are made possible by its automatic feature learning and high-volume modelling capabilities [29, 30]. The issues of limited intelligence and subpar performance in the analysis of enormous and heterogeneous big data can be resolved using DL approaches. It is possible to implement intelligent data processing, analysis, and decision-making control functions in smart fish farming by fusing the IoT, cloud computing, and other technologies [31, 32].

The model, RF, has an accuracy of 88.4817 percent, a weight of 88.5 percent for the average TP rate, and a standard of 87.11 percent for kappa statistic. These three metrics produce a superior outcome. The model, RF, has an accuracy of 88.4817 percent, an average TP rate weight of 88.5 percent, and a kappa statistic standard of 87.11 percent.

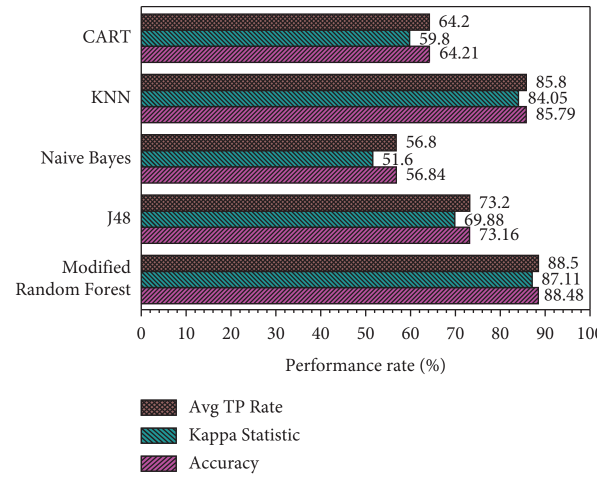

Figure 2: Average TP rate, kappa statistic, and accuracy for various models compared with modified random forest model.

These three metrics outperform various state-of-the-art models in terms of performance criteria when compared to the suggested model. The experimentation used five models: random forest, J48, Naive Bayes, KNN, and CART. Figure 2 shows a full comparison of all of the models. Figure 2 demonstrates that random forest (RF) has the best accuracy (88.48%) followed by the true positive (TP) rate (88.05%) and kappa statistic (87.11%) compared to all the metrics. The KNN model, with an accuracy of 85.79 percent, a kappa statistic of 84.05 percent, and a TP rate of 85.8 percent, has the second highest score. With an accuracy of 73.16 percent, a kappa value of 69.88 percent, and a TP rate of 73.2 percent, J48 takes third place. With accuracy of 64.21 percent, a kappa value of 59.80, and a TP rate of 64.2 percent, CART is ranked fourth in terms of scoring performance criteria. With an accuracy of 56.84 percent, a kappa statistic of 51.60 percent, and a TP rate of 56.88 percent, Naive Bayes (NB) receives the minimum score. The performance of NB is the least. The model, RF, has an accuracy of 88.4817 percent, a weight of 88.5 percent for the average TP rate, and a standard of 87.11 percent for kappa statistic. These three metrics have produced a superior outcome.

The main focus of the author was to determine the most accurate forecasting model for farmers cultivating fishes in an aquatic setting utilizing a variety of aquatic characteristics. The dataset's parameters were pH, temperature, and turbidity as well as fish, with temperature, pH, and turbidity designated by feature variables along with fish designated as the goal variable. A total of 11 different kinds of fish were used. Katla, shing, oyster, rui, koi, pontoon boats, zebrafish, carps, padre, magur, and shrimp are some of the fish available. As performance metrics, we look at accuracy, kappa, and TP rate. Five machine learning models were examined in all. Random forest (RF), Naive Bayes (NB), K-nearest neighbor (KNN), CART, and J48 are the algorithms in question. The random forest model has the best accuracy among these models [33].

Quality of water (WQ) is a critical factor in determining the success of freshwater pond extraction. In ponds, unpredictable and nonperiodic changes several WQ parameters which can affect growth and survival as well as efficiency of livestock in the water. Machine learning (ML) has evolved in tandem with modern sensor technologies to aid in today's technological transition in agricultural practice. As sensors and the Internet of Things (IoT) have now become popular in recent years, large amounts of agricultural data with a variety of modalities as well as spatial variations are collected from a variety of places. Aquatic cattle development in freshwater ponds has been observed to be limited by quality of cultivated water. As a result, a crucial part of aquaculture cultivation is maintaining WQ variables within optimal boundaries while conforming to industrial norms. The overall harvest outcome from ponds is assumed to be affected by dissolved oxygen (DO), saltiness, pH, temperature (Temp), turbidness, nitrite, ammonia water, and other WQ variables. It is critical to keep an eye on these WQ variables on a regular basis to ensure a strain-free climate improving livestock growth as well as survival. Poor WQ caused by many interactive variations in the developing environment for a long duration jeopardizes cattle development and survival, as well as making them susceptible to various infections. In aquaculture farming, water management is critical to increasing production productivity, as well as the quality and health of the animals. One of the main causes of aquatic disease outbreaks and significant crop mortality is WQ degradation. However, because the value of cultured water has been influenced by various interacting elements present in the environment as well as farm operating tasks, reliable prediction of diverse WQ characteristics is difficult. An automated system that forecasts WQ needed by a freshwater fish farm using DT. Rana, Rahman, and Hugo estimated WQ characteristics (temperature and conductivity) for two different maritime environments using four machine learning models (NNs and SVMs). ML models have also been used to investigate noninvasive approaches for evaluating the biomass size and growth, as well as aquaculture behavior tracking to eliminate physical injury or strain to aquatic livestock. A DL technique is used in gathering fish dimensions along with estimation of their mass, for example, may be used in a controlled environment. They estimated dimensions as well as eccentricity from high-resolution images using a CNN framework in an encoder-decoder architecture followed by building a correlation-based single variate model for forecasting the fish weight using a correlation-based linear model. Figure 3 shows that using growth as a performance indicator makes it easier to distinguish between high and low performing ponds (the target variable). The size of training data set could be one of the causes for the higher classification accuracy for the growth metric (i.e., no. of input-output references). Considering growth as a performance indicator (the goal variable), the data set has 43 input-output samples (i.e., 43 ponds having labels of low and high), whereas yield only has 32. The data set for the latter case had a smaller number of input-output examples, which may be lacking a set of ML models. Figure 4 provides the performance score of all WQ variables as well as ranking based on individual harvest variables. When growth is used as harvest metric, the results suggest that temperature and salinity are the two most critical WQ factors. Considering yield as harvest metric, however, DO as well as Temp are the top WQ factors. The most influential WQ factors are discovered to be Temp, DO, and salinity. These WQ variables have a much higher average merit score than the other factors. Considering growth as harvest metric, the average merit score for top-ranked variables is found to be 0.91 and 0.96 compared to 0.15 and 0.37 for other variables as shown in Figure 3.

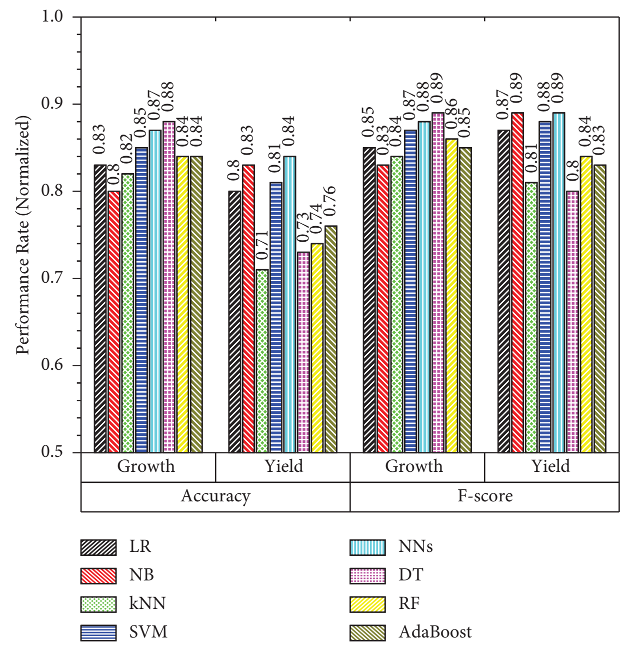

Figure 3: Comparison of the suggested model AdaBoost for classification performance in terms of accuracy and the *F*1 score of various ML algorithms using growth and yield metrics while taking into account the combined influence of all water quality indicators.

The same is true if yield is used as the harvest parameter rather than growth as shown in Figure 4. The ML techniques demonstrated considerable promise for generating decision assistance required by aquaculture farmers in order to indorse effects that result in high-performing ponds and avoid the situation that leads to low harvest outcomes. Because the methodologies presented in this paper are data-driven, they can be used to run trials and generate findings using farm-specific data [34].

In biofloc farming, it is unavoidable to be more sophisticated in terms of real-time water quality monitoring and precise feeding. However, the proportion of bacteria in the aquatic environment may be disrupted as a result of actual water quality monitoring, reducing the disease-resistant capabilities of the fish. Food prices can be cut using biofloc technology, and labor expenses can be cut with a smart aquaculture system. It is a good option because it is less expensive and better for the fish's health. Traditional fish farming causes a slew of other issues, including atmospheric Co2, ammonia, and nitrogen contamination in the water supply. Detoxification necessitates external filtration, which is both expensive and time consuming. Technology of biofloc is a great substitute for the traditional aquaculture

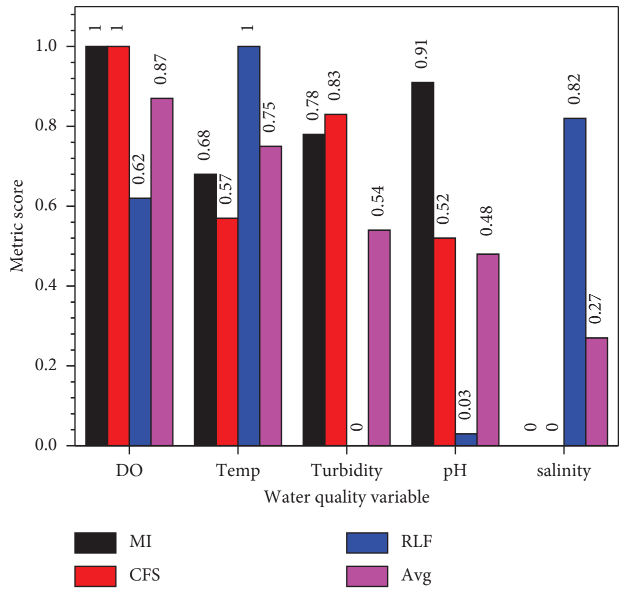

Figure 4: Considering yield as the major indicator, the effect of water quality factors on harvest result.

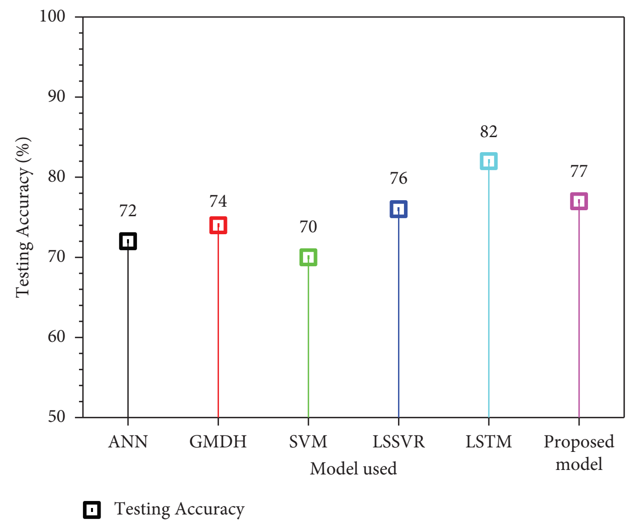

Figure 5: Comparison of testing accuracy of the different models.

method, which is both cost-effective and efficient. The usage of external instruments or substances may be reduced because biofloc helps to filter the water naturally. Biofloc is a low-cost fish rearing method that was recently introduced in aquaculture. Bioflocs are used to convert organic waste nutrients into reusable food. Since nutrients may be continuously reused and recycled in the culture medium with little to no water exchange. Biofloc technology (BFT) is regarded as a new "blue revolution." BFT is an aquaculture method that is beneficial to the environment and relies on in situ microbe production. The biofloc technology reduces feed consumption by 30% through the recycling of metabolic waste. Traditional aquaculture requires frequent water exchanges, which wastes water and increases costs. Biofloc lessens the requirement for water exchange. The water is filtered via a thin layer of bacteria, microbes, and algae which are helpful in nature. Bacteria are produced for this approach because they create flocs or algae, which break down ammonia and reduce pollutants in the water. Growing veggies and fish in the same yard using the biofloc approach can be beneficial. Tanks, air supply pumps, and 24-hour electricity are required for this procedure. Sensor development has reached a new level thanks to IoT innovation. IoT systems work with a variety of sensors to offer various types of data and information. It assists in the collection, transmission, and distribution of data to a network of similar devices. The obtained data enable the devices to act independently, and the entire environment becomes "smarter" every day. The phrase "Aquaculture Using IoT" refers to the utilisation of a variety of sensors, including those for dissolved oxygen, temperature, ammonia, and salt, but it is expensive and time consuming to maintain several sensors. The Internet of Things (IoT) is a rapidly expanding technology that is currently expanding its reach in all fields. Due to the rising global demand for fish and fish-based foods, aquaculture is one of the industries that is flourishing in many nations. The "2012 State of World Fisheries and Aquaculture" report from the United Nations Food and Agriculture Organization (UNFAO) estimates that 128 million tonnes of fish are produced worldwide each year. About 15% of people consume animal protein, which increases the need for fisheries [35].

Many researchers have focused on biofloc technology that is intelligent. Most studies use pH, DO, BOD, COD, NO3-N, and NH3-N as reference metrics for assessing water quality and changes. SVM, least-squares support vector regression, and artificial neural network (ANN) along with group method of data handling (GMDH) and super short-term memory (LSTM) have been popular techniques, and the testing accuracy has been compared for the various works as shown in Figure 5. The SVM model shows lowest testing accuracy (70%), while the LSTM model shows highest accuracy (82%). It has been observed that the proposed model shows good testing accuracy. The proposed model shows 77% accuracy, and only the LSTM model shows highest accuracy than the proposed model. The GMDH and LSSVR models show accuracy in between the others testing models. Furthermore, other designs relied solely on microcontrollers as well as sensors. Although projects are found to be cost-effective, they cannot predict WQ or health of fishes in the pond therefore able to automatically process solutions. The manual functions will require the support of a caretaker. In this work, the author suggested and implemented a mechanism to assist fish farmers in increasing fish productivity while lowering feeding costs. It is not necessary to use bigger ponds or a larger area [36].

Salinity levels that exceed the tolerance levels in various types as well as species of livestock, for example, severe impacts on physiology, result in reduced survival as well as growth. The aquaculture business still confronts obstacles such as the development of improved monitoring systems, the early detection of outbreaks, enormous mortality, and encouraging sustainability, and finding answers to these issues is a work in progress. The Gaussian distribution model has been proposed by Silva et al. [24] for detecting harmful operating circumstances in commercial fish farming. This study focuses on monitoring technology as a possible solution to these concerns. This method allows to see when production of fish is normal, warning, or dangerous using a 2D picture display. Furthermore, the mathematical technique outlined allows to identify the mathematical and statistical architecture of physical, chemical, and biological systems governed by suggested method, which has prospective applications in a wide range of fields of study. For the first time, this article describes that the newest technologies are must for computing as well as 5G technology in development of an intelligent fish farm, as well as the ecosystem. Carnivorous fish decline disturbs the food chain. Long-known contributors to the suffocating algal blooms that block sunlight and destroy ecosystems are nitrous fertilisers and detergent, but a new study shows that overfishing of large fishes is also a significant factor. Algal blooms in our area typically come in three colours: red, brown, and green. Phytoplankton with the reddish pigment peridinin is what causes red tides. The ocean usually becomes crimson during a bloom of this dinoflagellate. Pelagophytes, a different class of microalgae, including *Aureococcus anophagefferens*, are responsible for brown tides. *Phaeocystis*, a globally distributed unicellular photosynthetic algae, is capable of producing green tides.

Human-caused nutrient pollution makes the issue worse by causing more frequent and intense blooms. Algal blooms happen when an excessive number of algae grows because of the entry of nutrients such as nitrogen or phosphorus from multiple sources (such as fertiliser runoff or other types of nutrient pollution). The entire ecology is affected by an algal bloom. The consequences can be beneficial, such as feeding greater nutritional levels, or negative, such as preventing other creatures from receiving sunlight, depleting the oxygen in the water, or secreting toxins into the water, dependent on the organism.

The major intelligent machinery of smart fish farm has been specified next, and technical qualities are examined based on the system's hardware setup. Recent research at home and abroad has been summarised in terms of water quality advance detection and control, intelligent fish feeding, monitoring of fish behaviour, estimation of fish biomass, diagnosis of fish disease, diagnosis of equipment fault, and design scheme of relevant business components of the intelligent fish farm. Presented paper outlines the obstacles and research centers in developing smart fish farms, with the goal of providing aquaculture experts with the most up-to-date, comprehensive, and authoritative thoughts on future fishery building.

Traditional smart mariculture systems were not always tough in adapting the complex and changeable as well as uncertain environment present in open waters, but they will face a few problems, including poor accuracy along with high temporal complexities as well as poor forecasting. To address the discussed issues, the novel TCN-based WQ forecasting system was developed to estimate dissolved oxygen, water temperature, and pH. Using dilated causal convolution, the TCN forecasting network is able to extract time series features along with in-depth data properties, and it has a good long-term prediction impact.

Experiments have shown that TCN-basedlong-term forecasting methods have superior accuracy as well as time complexity compared to RNN (the recurrent neural network) as well as SRU (the simple recurrent unit). Traditional prediction techniques for water quality prediction include the time series method, the Markov chain method, the regression analysis method, the grey theory method, and the support vector machine.

They only require a little quantity of previous data, but they have several flaws, including low prediction accuracy and a lack of consideration for various aspects, such as air temperature. Artificial neural networks and deep learning techniques are more robust and accurate than standard algorithms, and so they can adapt to a variety of challenging contexts. These approaches nevertheless have flaws, such as a complicated network topology and high time difficulty, which raises hardware needs. The imperfection and volatility of correlation analysis can be solved using the spatial cross-correlation analysis approach in combination with spatial distribution information, especially if the sample size is insufficient.

The projected data are near to the true values, as shown in Figure 6; however, the TCN model performs best at adjusting the actual data pattern when estimating maximum and trough values. Simultaneously , the TCN model appears to be significantly smaller in the test dataset.

As a result, the TCN forecasting model predicts water quality metrics more accurately. Because the TCN prediction model uses a residual network structure to tackle the differential attenuation problem, it can investigate the deep network's features, giving it a good fit and generalization ability. We will focus on improving the deep learning network structure and incorporating peak prediction modules in the future. In addition, this work will gather years of water quality data as the training dataset in the future research to make the water quality forecasting model more resilient and reduce the effects of climate change on the forecasting model. Simultaneously, it will incorporate several factors as previous information into the deep neural network, including seasonal swings and climatic changes, for the prediction model to accomplish long-term predictions [37].

Fish mortality, especially due to outbreaks, is a big burden for aquaculture producers and has a considerable influence on production. During the previous decade, a tremendous deal of efforts was gone into developing solutions. For example, outbreaks have long been researched to better understand important clinical and epidemiological aspects of infection and to identify the etiological agents. Some of the successful control strategies for minimizing high levels of mortality include disrupting bacterial quorum sensing, sample timing and surveillance, remote physiological monitoring, long-term monitoring, increased rearing, and postbiotic therapies. Nitrite levels above a certain threshold induce severe physiological abnormalities and widespread fish loss. Nonetheless, the amount of nitrite needed to kill fish varies by species, and the occurrence of mortality may be delayed. Nitrite levels above a certain

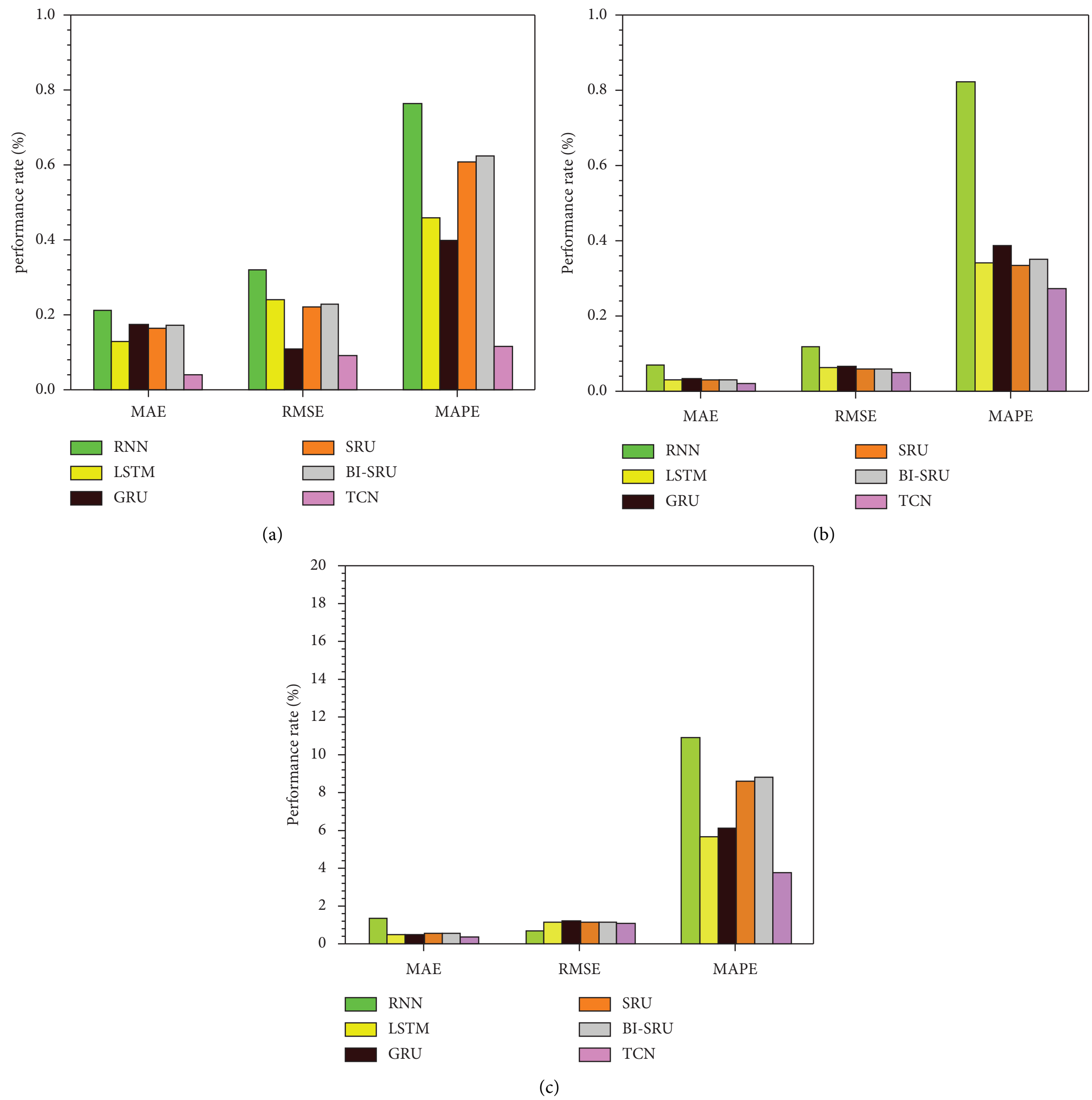

FIGURE 6: Performance rate for several models for (a) water temperature, (b) pH, and (c) dissolved oxygen as water variables.

threshold induce severe physiological abnormalities and widespread fish loss. Nonetheless, the amount of nitrite needed to kill fish varies by species, and the occurrence of mortality may be delayed. To boost fish production, aquaculture facilities have improved to the point where they can monitor many physical parameters at once to fulfil a wide range of operational needs, including hardness, alkalinity, bromine, nitrogen dioxide, pH, ammonia, salinity, and temperature, among others. A Gaussian distribution model for detecting dangerous operational conditions in aquaculture facilities in this work has been presented to develop a new way that can indicate the current state of the fish hatchery while avoiding high mortality rates and assisting in the building works of positive changes in aquaculture practices.

The fish mortality rate was used as a demarcation criterion in the Gaussian distribution model, which gives three distinct working environments: normal, warning, and dangerous. The decision to use this parameter as a separating boundary is based on two main reasons. It has been mentioned in the introduction that one of the key problems of fish growers in numerous nations is mortality. Second, several physical factors such as temperature, pH, nitrite, ammonia, salinity, alkalinity, and bromine are measured on a regular basis, and a severe health situation for fish does not develop with a change in just one of these parameters, as changing one modifies others as well. The Gaussian probability density curves that describe each of the three possible system parameters of fish farming were layered sequentially according to their standard deviation for a better visual perception of the presented model, and the image formed by the isometric view of these curves creates the visualization of the Gaussian distribution model. It is crucial to note that the physical and chemical monitoring metrics that determine the water quality in the fish tanks have various values depending on the stage of development of the fish. Moreover, despite this discrepancy, the scientific formula can successfully illustrate that the system works regardless of the stage of fish development. One of the main problem in aquaculture is efficient water quality management, which helps to guarantee high fish production and quality. Monitoring is necessary since there are four major factors that influence the water condition and have an impact on aquaculture cultivations. These consist of pH, temperature, salinity, and dissolved oxygen. These factors need to be maintained at all times within predetermined thresholds in order for the fish to remain in the best possible health and to prevent stress or disease.

3. Discussion

The technical specifics of DL and ML-based adaptive fish farming techniques, including data, algorithms, and performance, are explored. The capacity of DL/ML to consistently extract features is the most major contribution, according to the review results. DL/ML is still at a primitive artificial intelligence stage as well as requires vast volumes of the labelled training dataset that has become a constraint which limits future DL applicability in aquaculture, despite various challenges and constraints. With the development of numerous technologies, such as motorised machinery and biotechnology, agricultural has continuously improved. The agriculture sector is adopting AI technology to increase efficiency in line with commercial trends. With the use of agricultural AI, farmers can examine data acquired from their farms on weather, temperature, water use, and soil conditions to make educated decisions about their businesses, such as choosing the most practical crops to grow that year or which hybrid seeds reduce waste. Big data analysis also pinpoints the precise soil, light, food, and water requirements required for development and determines optimum irrigation. It also aids in lowering greenhouse gas emissions.

DL, on the other hand, continues to provide advancements in dealing with complicated data in aquaculture. The critical review's major goal is to give academics as well as practitioners a healthier grasp of the present state of the art on deep learning in aquaculture and may help them deploy smart fish farming applications. For irregular target detection in difficult situations, such algorithms provide great accuracy and stability. They are trained to learn mappings as well as correlations among samples along with the items present in those samples with ease. The studied models are capable of not only monitoring unknown items or abnormalities but also predicting factors such as water quality with greater accuracy and precision. More computer power and longer training durations are required for DL models. The capacity of deep learning models to learn and improve over time is still limited, as is their interpretability when working with imbalanced training data.

Incomplete data is another key setback. Preprocessing the data is a common yet time-consuming operation. High costs for those involved, such as AI technicians or farmers, as well as a large number of sensors, high computational power requirements, and costly equipment are also an constraint.

4. Conclusion

The present uses of DL for smart fish farming were investigated in depth and comprehensively in this research. The present applications may be categorized into various groups based on a survey of recent literature, namely, fish classification, precision feeding, dissolved oxygen, and other water quality variables monitoring. The technical aspects of the given approaches were thoroughly examined in light of AI's two most important components: data and algorithms. The LSTM model has the highest testing accuracy (82%), while the SVM model has the lowest (70%). The proposed model has been examined and found to have good testing accuracy. Only the LSTM model exhibits more accuracy than the suggested model, which has a 77% accuracy. The accuracy of the GMDH and LSSVR models is higher than that of the other testing models. When compared to older approaches that rely on manually extracted features, the capacity of ML/DL to extract features automatically is the most significant advancement. DL is also capable of producing high-precision processing outcomes. It is similarly projected with an extend domain of a new field of applications including fish illness diagnostics; data have become more significant as well as composite models which can take into account the spatiotemporal sequences in the fundamental research directions.

In summary, the goal of this study was to give academics and practitioners a healthier grasp of present uses of DL in smart fish farming which makes it easier to apply DL technology to solve actual aquaculture challenges.

Data Availability

Data will be made available upon reasonable request from the corresponding author.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding the publication of this article.

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