



Integration of Information Technology in a Compact Neural Network Model for Real-Time Monitoring of Seagrass

Atyaf Sami Noori^{1,*}

¹University of Information Technology and Communications, Baghdad, Iraq

Email: dr.atyaf.sami@uoitc.edu.iq

Abstract

Monitoring seagrass ecosystems offers critical insights into water quality, which is essential for maintaining aquatic biodiversity. Real-time monitoring, however, is hindered by various challenges, including coral reef degradation, habitat deterioration, fishing impacts, seagrass dredging risks, and complex coastal management issues. To overcome these barriers, this study presents an improved neural network model enhanced by Information Technology (IT) and Artificial Intelligence Neural Networks (AINN). Specifically, a recurrent neural network (RNN) has been utilized to address fishing pressures and habitat issues by evaluating sediment stability within seagrass areas. Additionally, a modular neural network (MNN), leveraging IT support, effectively analyzed coral reef deterioration to promote ecological sustainability. A convolutional neural network (CNN) was further implemented to enhance risk assessment and facilitate optimal seagrass growth conditions, thus improving real-time monitoring accuracy. Results indicated that this integrated IT-based neural network significantly surpassed traditional CNN methods, achieving superior performance in seagrass monitoring and coastal ecosystem management.

Keywords: Seagrass; Ocean; Neural network; AI; Information technology

1. Introduction

Coastal blue carbon ecosystems like mangroves, salt marshes, and seagrass meadows play a critical role in an environment that provides habitat for fisheries, performs water purification, enhances soil stability, reduces coastal erosion, supplements nutrients, protects coastlines, and supplies nutrients [1]. Natural service by seagrass includes production, biogenic habitat creation, water filtration, wave energy attenuation, and silt entrapment in sea areas [2]. Seagrass distribution maps may be rebuilt by the data collected during the field. Executed stratified field sampling enables synoptic assessments of these attributes, but airborne and satellite remote sensing does not allow for spatial generalization of the finer aspects [3]. Seagrass species' growth strategies are classified by the biomass of belowground tissue in their species. Alligators' natural selection through excavation is among the environmental services that seagrasses supply [4]. Seagrasses are important sources of food and habitat for marine life and one of the most effective carbon sinks. Technology and particle developments have enabled an enormous rise in a dissertation that access if seagrasses are affected by ocean warming [5].

The seagrass beds are essential to the health of our oceans. Aside from the increased production and export of organic carbon and nutrient cycles. The sediment stability helps coastal marine ecosystems maintain their richness and facilitates tropical interactions between nearby habitats. [6]. the seagrass ecosystem serves as a spawning site, nursery ground, and carbon sink for various economically valuable species. The seagrass bed ecosystem also serves as a sediment trap, which helps to keep the water clean so that coral reefs can flourish [7]. Land reclamation, development, and coastal engineering are combined with the indirect stresses of climate change and sea-level rise, and seagrass meadows perform an array of important ecosystem services. Nevertheless, these meadows are highly prone [8]. The quiet waterways on the west coast, protected from the open sea by the tidal sand ridges, are ideal habitats for seagrasses [9]. Seagrasses are rooted vascular flowering plants that originate on land and grow in shallow coastal environments, frequently forming meadows. Habitat building species in shallow soft sand depend

strongly on them, and they play a vital role in the coastal ecosystem [10]. Seawater, temperature, and light availability at depth always had a massive effect on seagrass biodiversity. The lagoon's seagrasses are in peril [11]. The seagrass as a bio-fertilizer for plant development and yield was the objective of this project. Water and soil quality is harmed by the excessive use of commercial chemical fertilizers and pesticides [12]. The ecological services are provided by temperate and tropical estuaries' coastal habitats. Seagrasses and oyster reefs mangroves can work together to protect the shoreline in the estuaries [13].

An ecologically appropriate load objective for the case study of seagrass meadows is to evaluate the link between catchment sediment flows and access them against the water quality improvement plan ecological targets [14]. The ecosystem services provided by coastal marine ecosystems are critical to human well-being, such as food production, coastal protection from storms and floods, water purification, nutrient cycling, carbon sequestration, tourism, and recreational and spiritual effects [15]. Seagrass seed bank analyses were paired with yearly assessments of seagrass distribution to explore seed bank spatial patterns and their relationship to seagrass recovery presence and water depth. [16]. Aquatic salinity gradients are projected to be altered by extreme climatic events, exposing organisms that construct habitats to more frequent salinity fluctuations [17]. Seagrass ecosystem monitoring is critical to the effective and long-term management of coastal waterways. Now, seagrass meadow maps are created by combining data from various methods [18]. Organophosphate pesticides are persistent in the environment, although little information is available on their bioaccumulation in seagrass. These chemicals eliminate pests that affect plants or animals [19]. Restoration efforts are progressively slowing the degradation of coastal ecosystems. Designs that reduce physical stress and competition have dominated coastal habitat restoration efforts [20]. The green turtle fishing industry in the waters of Texas with a current average harvest of regarding turtles. This sea turtle ecology was subjected to inevitable stressors due to human activity. [21].

Environmental harm affected human activities, like trawling for fish, mining and agricultural wastes, urban and industrial waste, coastal structures, beach replenishment, and aquaculture burdens [22]. The Mediterranean region's seagrasses seemed to decrease rising sea levels related to ocean warming and ice sheet melting, with resulting variations in oxygen concentrations based on temperature shifts [23]. Seagrass carbon sinks in the Mediterranean Seagrass Ocean meadows are becoming more fragmented, increasing the number of wildlife declines [24]. Seagrass science has evolved from a descriptive area to a quantitative and predictive undertaking that demands a mechanical knowledge of the environmental effect on metabolic networks that govern energy uptake, development, and reproduction [25].

The main objective of this study are:

- To promote the degradation of the natural environment based on AINN supports commercial fishing and biodiversity, reduces carbon dioxide, and restores the natural environment from the atmosphere. Seagrasses are an essential part of the ecosystem.
- A recurrent neural network (RNN) is a specific artificial neural network designed to operate and reduce seagrass dredging. It can significantly increase the amount of light reaching the seagrass.
- Modular neural networks (MNN) enable the risk of improper coastal zone management and control risk. The numerous interact together as modules, each handling a specific problem.
- Without human intervention, a conventional neural network (CNN) can automatically identify the essential elements. This balance can increase marine life, particularly fragile species like sea turtles and corals, by reducing overfishing.

The remainder of the article is section 2, which indicates a literature review on improving the use of seagrass monitoring. Section 3 denotes the improvement of the neural network model in the real-time compact tracking of the health of seagrass in AI. Section 4 mentions results and discussion on realistic and portable neural network modeling in real-time; section 5 delivers the seagrass monitoring application and concludes this essay.

2. Related Works

Len J. McKenzie et al. (2021) detailed that large and diverse seagrass habitats dominate the area. The Pacific island countries and territories have seagrass habitats (PICT) [26]. There were certain PICTs in the eastern Pacific that documented seagrass species. Seagrass ecosystems across the world are under threat from human activity. Seagrass habitats are ignored by conservation policies and regulations in the region's oceans, dominated by efforts to protect coral reefs. It is possible to improve the resilience of seagrass ecosystems via the involvement of local people in resource management and the reduction of damaging behaviors.

Brandon Hopley et al. (2021) proposed multi-spectral sensors that have made it possible to scan seagrass meadows at extremely high resolution, significantly improving ecologists' ability to monitor changes. A fully convolutional neural network (FCNN) is a growing collection of deep learning techniques [27]. An optical drone survey of seagrass and other coastal elements was used to show the efficacy of FCNN in a semi-supervised situation. Tidal

fluctuations have an important influence in determining the health and dynamics of coastal habitats, and intertidal seagrass has no exception. It is useful for remote sensing applications, and data remains an expensive commodity. Lucia M. Fanning et al. (2021) introduced this article to evaluate the possible use of the ecosystem-based management (EBM) framework and to sustainably manage coral reef and seagrass bed ecosystems in light of present natural and human concerns and the resulting predicted loss in ecosystem services [28]. Scientific planning and valuation of the marine environment, reframing and crafting regulations, rules, policies, monitoring and enforcement of laws, and promoting public knowledge and involvement are vital aims for implementing EBM stated by stakeholders. The existing level of understanding about coral reef and seagrass ecosystems and the advantages that a subset of the population derives.

Subhash Chand et al. (2021) developed human and climate implications that are causing seagrass meadows to collapse locally and worldwide. Utilizing spectral indices and supervised machine learning classification, the remotely piloted aircraft system (RPAS) identifies fine-scale seasonal seagrass variations [29]. Temporal and spatial changes in this dynamic coastal environment were documented using low-altitude, local remote sensing time series data. According to the results of the time-series seasonal change detection, seagrass meadows decreased in quantity and distribution from summer to autumn. Seagrass meadows increased in abundance and dispersion from autumn to winter. This investigation made a vital contribution to document seasonal changes in marine ecosystems.

Ben French et al. (2021) initiated that world fisheries depend on seagrass fishes and play an essential part in the ecosystem. The sustainable management and maintenance of seagrass fish communities rely on reliable approaches. The distinct components of the fish assemblage, baited remote underwater video (BRUV) [30], demonstrated a better power to identify changes in species richness of seagrass fishes. The approach actualized to gather data on seagrass fish abundance and variety significantly affected the results.

Chiaki Yamato et al. (2021) the curved pathways left by species after consumed have been considered an indication of the dugongs' feeding site implementation. It takes significant time and effort to measure the trails on the ground and create practical methods for observing the dugongs' feeding trails in an unmanned aerial vehicle (UAV) [31]. UAV surveys benefit from conducting surveys with a variety of frequencies, and the researchers can monitor daily, tidal, and seasonal dynamics depending on their goals.

Jessica Pazzaglia et al. (2021) introduced the marine flowering plants classified as seagrasses that play an essential role on beaches and waterways worldwide. Restoration of disturbed seagrass settings has become a worldwide priority to reverse the ecosystem [32]. Deterioration and regaining ecosystem functionality and associated services increase human activity in the oceans and coastal areas. This developed a discipline of epigenetics in seagrasses that require more significant research to improve restoration and conservation efforts.

I Riniatsih et al. (2021) detailed that Seagrass habitats in the region were particularly sensitive to climate change. Similarly, ecological surveys performed on the ground by remote sensing from satellites and aircraft platforms have been used to monitor species in reduction and assess their vulnerability to various human-caused threats, particularly global climate change. [33]. the object-based categorization method provided effective and efficient results. For the different picture resolutions, it was required to undertake a more in-depth analysis of the parameter scale utilized to generate a better accurate segmentation of the image.

Susana Lincoln et al. (2021) initiated that human activities and climate change reduce the worldwide importance of seagrasses, which are vital to marine ecosystems [34]. According to seagrass measurements, there was a more significant concentration of dissolved inorganic nitrogen and suspended particles in the seagrasses. Seagrass cover and height varied widely throughout the sites surveyed, indicating that the meadows were usually patchy and various species and sizes.

W Lazuardi et al. (2021) developed marine ecosystem services, as biodiversity preservation, erosion control, fishery, and tourism depend on coral reefs and seagrass on the shore [35]. The percent cover mapping is a hard use of remote sensing. Coral reefs and seagrass provide a wide range of essential economic and environmental advantages for people and their lives. Remote sensing data is quite precise and may be used as a reference or foundation for coastal management information.

Lillian R. Aoki et al. (2021) detailed that Seagrass meadows and associated sediment blue organic carbon (C) are under threat from rising ocean temperatures and heat waves [36]. Considering climate change and artificial stresses on ocean ecosystems, there is a limited frame of opportunity to restore sustainable and resilient coastal habitats and seagrass meadows. Large-scale and long-term restoration operations are more important than ever to enhance the advantages of blue Carbon storage in seagrass meadows despite the backdrop of rising climate change.

Shaochun Xu et al. (2021) proposed that despite the importance of maintaining a high level of biodiversity, seagrass meadows face constant threats from human activities like sea reclamation [37]. The quantity of reclaimed area increased seagrass meadows altered dramatically on the maps. Sea reclamation has been implicated as the primary cause of habitat loss in some seagrass meadows of the physical damage, excessive sedimentation, and increased turbidity it causes. On a vast spatial and temporal scale, the research can enable coastal managers to monitor the effects of reclamation activities on seagrass meadows.

Some of the drawbacks of artificial intelligence in seagrass monitoring are degradation of the natural environment, seagrass dredging, improper management of the coastal zone, and overfishing, which contribute to the above work. These disadvantages can be overcome with PICT, FCNN, EBM, RCAS, and BRUV to compare with the neural network in seagrass monitoring on the proposed method AINN.

3. Materials and Methods

Monitoring seagrass health provides essential information on water quality, which is necessary for the survival of aquatic plants and animals. To gauge the health of the seagrass, photosynthetic efficiency is a good indicator. Measures of photosynthetic efficiency, on either hand, are time and money consuming. A seagrass species, *Zostera Capricorn*, was studied in spectral reflectance data to assess photosynthetic efficiency. It is possible to expand the neural network-based strategy to seagrass species using a classifier and an ensemble of neural networks a classifier to identify a specific species of seagrass, and it is used to estimate photosynthetic efficiency to overcome the problem of degradation of the natural environment in the proposed method AINN technology.

3.1 Artificial neural networks in environmental deterioration:

The below diagram describes an artificial neural network in different processes of ecological deterioration.

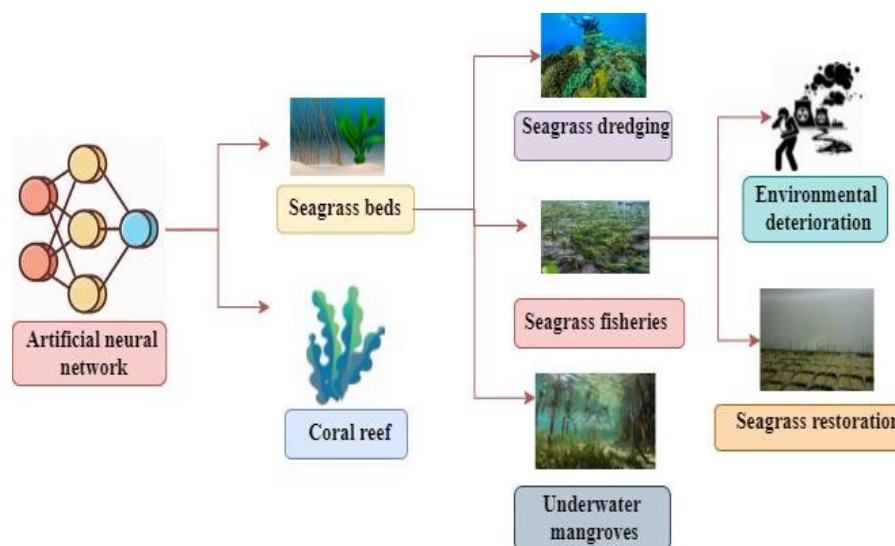


Figure 1. Artificial neural network in monitoring seagrass:

Figure 1, shows that artificial neural networks (ANN) are a virtualization technology based on human brain neural networks. A single-layer neural network has only one layer of input nodes that weighted inputs to the last layer of receiving nodes. A Multilayer perceptron contains input and output layers and one or more hidden layers with numerous neurons layered on top of each other for processing. The high productivity of coral reefs is already attributed mainly to photo symbiotic relationships between coral animals and algae of the family. The knowledge and the host can boost algal photosynthesis by concentrating nutrients and improving light absorption. Food security measures an individual's capacity to obtain healthy food. Shelter, water, food, and space are the most important aspects of habitat. The right balance of these elements in a habitat is attributed to a suitable arrangement.

Fishing for seagrass invertebrate species is an essential source of protein for some of the most vulnerable residents of tropical coastal communities. A mangrove is a plant or tree that thrives in coastal salty water. In addition, the label is used to describe tropical coastal vegetation that includes species. Services provided by invertebrates are crucial to human civilization and economic well-being. Among the benefits, invertebrates include pollination of crops and wildflowers, production and upkeep of healthy soils, and even the formation of new habitats.

3.1.1 The derivatives for artificial neural network:

$$\alpha(a) = \cos \varphi * \frac{p \sin \alpha}{p+p \cos \alpha} + \sqrt{\frac{\pi}{2}} p^2 + 2p^2 \cos \alpha + p^2 \int \mu \delta * \delta \tag{1}$$

As shown in equation (1), artificial Neural Networks are structured $\cos \varphi$ up by a wide range of $\frac{p \sin \alpha}{p+p \cos \alpha}$ layers from these units. The number of units in $\sqrt{\frac{\pi}{2}} p^2$ a layer can range from a few hundred to millions, depending $2p^2 \cos \alpha$ on the system's complexity. It's common for an artificial neural network to have an input, output, and $p^2 \int \mu \delta * \delta$ hidden processing layer, as represented in equation (2).

$$\alpha(b) = \int W \sin A \cos B + \sum \frac{\partial y}{\partial x} \iint \frac{1}{\varphi(1+\Delta)} f(x) \left(\frac{E+E^{-1}}{2}\right) \Delta^3 Y_2 \tag{2}$$

As shown in equation (2), growths of coral are attached to $\int W \sin A \cos B$ one other by calcium $\sum \frac{\partial y}{\partial x}$ carbonate, forming the underwater $\iint \frac{1}{\varphi(1+\Delta)}$ structures. Coral reefs are sometimes $f(x)$ considered the ocean's tropical rainforest of their richness and $\left(\frac{E+E^{-1}}{2}\right)$ diversity. In a wide range of food product quality inspection and grading applications, artificial neural network $\Delta^3 Y_2$ classifiers have been effectively deployed.

$$\alpha(c) = \log(1 + \Delta) = \log 2 \frac{1}{E} \sqrt{\frac{h}{1+hx+x^2}} + \iint \frac{\partial y \Delta^2}{\partial x E} + \left(\frac{\Delta^2 u_x}{Eu_x}\right) \tag{3}$$

As shown in equation (3), the capacity to learn patterns $\log(1 + \Delta)$ that are not linearly separable and $\log 2 \frac{1}{E}$ ideas dealing with $\sqrt{\frac{h}{1+hx+x^2}}$ uncertainty, noise, and random occurrences make them excellent pattern classifiers. In food product data analysis and classification, the $\iint \frac{\partial y \Delta^2}{\partial x E}$ multilayer perceptron trained to use the error back-propagation $\left(\frac{\Delta^2 u_x}{Eu_x}\right)$ technique for most used artificial neural network taken from equation 2, the next result is the recurrent neural network.

3.2 Recurrent neural network methods increase seagrass sedimentation in dredging:

Figure 2 denotes the development of seagrass sedimentation in dredging on the recurrent neural network method:

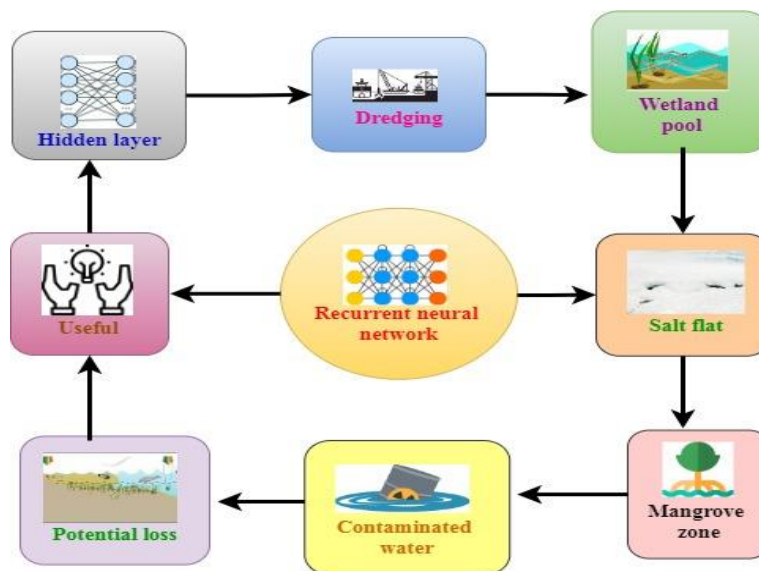


Figure 2. Recurrent neural network sedimentation in seagrass dredging:

Figure 2 shows a recurrent neural network (RNN) to emulate human processing patterns, and they evaluate the complete phrase instead of the individual words. In neural networks, a hidden layer sits between the algorithm's input and output, weights are applied to the inputs, and an activation function directs the output. Dredging is cleaning out the bottoms of large bodies of water by removing silt and debris. Sedimentation builds up in waterways and ports as sand and silt flow downstream. Wetlands are placed where water covers the soil, and it is

present near the soil's surface throughout the year or variable lengths of time throughout the year, including the growing season. A saltpan is a vast, flat stretch of land, originally a lakebed. It is common for salt flats to appear white due to the high salt concentration. Plant and animal populations of all kinds are found in the mangrove zone, encompassing the intertidal coastal region between the spring high tide line and the spring low tide line. The activity or scenario is substantially bound to generate waste is a potential loss.

3.2.1 The derivatives of a recurrent neural network:

$$\alpha(d) = (x^2 + QR) = \frac{QR(Q+R)}{Q^2+R^2-Y^2} \int P^2 + Q^2+R^2 + 2PQ \left(\frac{1+\mu}{2}\right) \tag{4}$$

As shown in equation (4), the operation of dredging material from the $(x^2 + QR)$ water environment to improve water features, reshape $\frac{QR(Q+R)}{Q^2+R^2-Y^2}$ land and modify drainage, navigability, and commercial usage that create dams and related $\int P^2 + Q^2+R^2$ controls for streams or shorelines. Wetland ecosystems for $2PQ \left(\frac{1+\mu}{2}\right)$ food and shelter, and services are valuable to society.

$$\alpha(e) = I^2 = m^2 g^2 + m^2 \frac{v^4}{r^2} \sqrt{1 + \frac{l}{g\delta} \int 2\pi \left\{ \frac{l}{g} \left[1 + \frac{1}{4} \sin \theta \frac{\gamma\alpha}{2} \right] \right\}} \tag{5}$$

As shown in equation (5), land has been submerged in $m^2 g^2 + m^2 \frac{v^4}{r^2}$ water is considered to be a wetland. As water filters, flood $\sqrt{1 + \frac{l}{g\delta}}$ and erosion control, and habitats for fish and animals, wetland habitats are crucial to an ecosystem's health. Natural water is $\int 2\pi$ derived from aquifers provided by permeable sands and soils $\left\{ \frac{l}{g} \left[1 + \frac{1}{4} \sin \theta \frac{\gamma\alpha}{2} \right] \right\}$ under the surface of the land.

$$\alpha(f) = 2 \sin \frac{ph}{2} + F \propto \frac{1}{2n+3} \cos \left[px + E + \frac{(ph+\pi)}{2} \right] \frac{x^2}{2} + x \iiint \frac{dy}{dx} \tag{6}$$

As shown in equation (6), the chemical particles $2 \sin \frac{ph}{2}$ that harm sea creatures can cause $F \propto \frac{1}{2n+3}$ a stream to become tainted and $\cos \left[px + E + \frac{(ph+\pi)}{2} \right]$ dangerous. Contamination of water can disrupt the water cycle in nature and have the opposite impact. Drinking water can be contaminated $\frac{x^2}{2}$ in a variety of ways. Chemicals, pesticides, animal waste, and industrial waste are all included in this category. It is possible $x \iiint \frac{dy}{dx}$ naturally produced chemicals contaminate that groundwater like arsenic and radon.

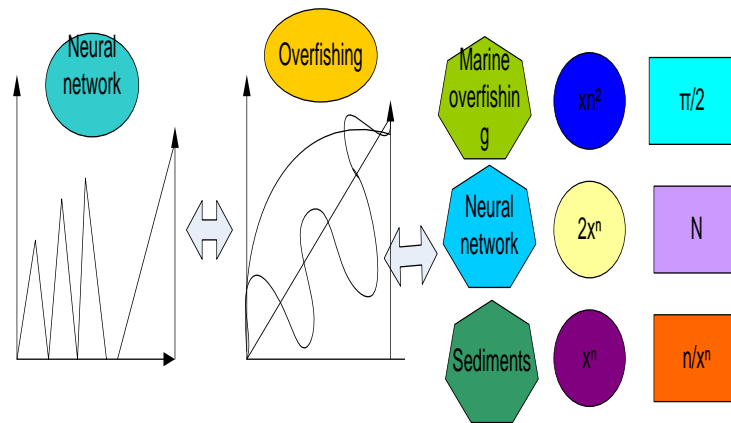


Figure 3. Mathematical framework of a neural network for preventing overfishing:

Figure 3 denotes that marine overfishing is prevented with a neural network.

Figure 3 shows several commercial fishing methods that harvest large quantities of undesired fish or other animals before discarding them. The small-scale fishers can generate information on fisheries and markets that helps to make better business decisions and demonstrate their commitment to ocean conservation. Several of the most significant ways to combat overfishing include reforms, subsidies, and a ban on fishing in particular sections of the ocean. Sustainable fisheries and fishing farms can be encouraged by individual consumer choices like the purchase of sustainably caught seafood. This study examines whether the catch weight is related to data gathered from all sensors deployed on fishing vessels. The sensors aboard fishing vessels train neural networks to forecast the weight of a catch, and random sampling techniques process raw data into a neural network for training.

$$Dy_n = \frac{xn^2+N}{2x_n} = \frac{\pi}{2} \left(x_n + \frac{N}{x_n}\right) f(x) \quad (7)$$

As shown in equation (7), In fishing, money is a powerful incentive $\frac{xn^2+N}{2x_n}$ that may encourage individuals to improve habits and support $\frac{\pi}{2} \left(x_n + \frac{N}{x_n}\right)$ the required management to decrease $f(x)$ fishing's environmental impact.

$$\alpha(g) = \sqrt{\frac{\pi}{2} p^2} + 2p^2 \cos \alpha \sum \sin(\theta + \beta) = \frac{\tan \alpha \sin \beta}{\mu} \iint \frac{u \sin \alpha}{u+u \cos \theta} \quad (8)$$

As shown in equation (8), overfishing can be alleviated by capturing fish $\sqrt{\frac{\pi}{2} p^2}$ at the base of the food chain. The least demanded fish are $2p^2 \cos \alpha$ tuna and salmon are at the top of the food chain, and the majority of them are enormous ocean predators. Fish stocks $\sum \sin(\theta + \beta)$ have been decreased because of overfishing. Anglers $\frac{\tan \alpha \sin \beta}{\mu}$ catch a lot of seafood, and it's difficult to $\iint \frac{u \sin \alpha}{u+u \cos \theta}$ restore the fish populations in the oceans.

3.3 Modular neural network in real-time monitoring seagrass application:

Figure 4 denotes the real-time monitoring seagrass application in a modular neural network.

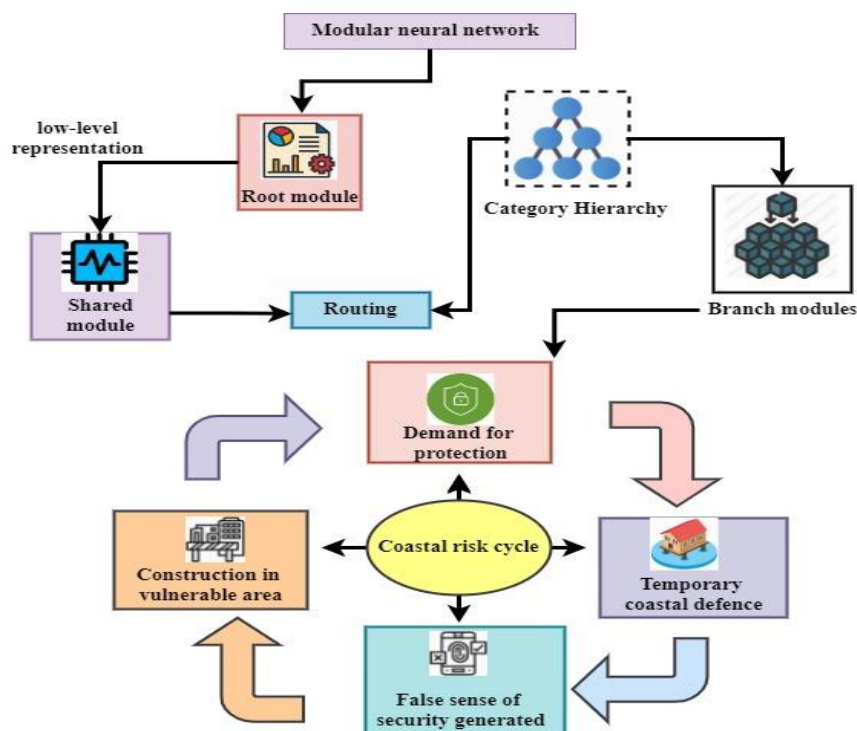


Figure 4. modular neural network for coastal zone management:

Figure 4, shows a modular neural network composed of several separate neural networks controlled by a third party. The physical nature of the input dictates low-level representations, and high-level models converge across multiple low-level representations that designate the same objects or events. A Shared Module is used to group several frequently used elements into a single module and export to any module that imports the share module. Data is breached as a system operator cannot recognize or consent to the theft or removal of information from the system. Structures including groynes, seawalls, bulkheads, breakwaters, and jetties indicate coastal protection structures. Physical, economic, institutional, and human variables all have a role in determining a person's vulnerability. It changes with time, space, and the unique characteristics of the ground floor of the building that is located. Storm tides, river floods, stormwater runoff, coastal constructions, and sea-level rise all contribute to erosion and instability of the coast, from storm tides to wave overtopping to river flooding to the tsunami and rising sea levels. Category hierarchies categorize goods, suppliers, and other data for reporting and analytical purposes. Each hierarchy possesses a parent category and a subcategory critical as child categories.

3.3.1 The derivatives for the modular neural network:

$$\alpha(h) = \left(\frac{y(x+h)-y(x)}{h}\right) \sum \frac{\pi}{2} \int \frac{x-x^0}{2h} + \left(\frac{x-1}{h} - 1\right) \frac{dy}{dx} \tag{9}$$

As shown in equation (9), coastal zone management requires balancing human, environmental, economic, and health-related factors in coastal zones. It encourages coastal states and territories to engage with the federal government to establish and implement community programs consistent with federal policies.

$$\alpha(i) = \frac{xn^2+N}{2x_n} = \frac{\pi}{2} \left(x_n + \frac{N}{x_n}\right) + \left(\frac{(p-1)x_r+a}{pxr_n}\right) x_{y^2} + \frac{1}{2} \delta^2 + \delta \tag{10}$$

As shown in equation (10), a modular neural network consists of a neural network model that is connected by an intermediate or as a graph. Complexity may be achieved by combining more basic neural network systems with greater advanced modules. A shared module is crucial if the project is large and has several modules.

$$\alpha(j) = h \left[1 + \frac{E-1}{2}\right] f(a) \sqrt{1 + E - 1 + \frac{(E-1)}{6}} \iint \frac{y_3-y^1}{6} = \frac{2h}{3} \tag{11}$$

As shown in equation (11), angular application with modules and various components is used throughout. In this circumstance, importing all components into every module or app module is not smart. Coastal protection infrastructure is increasingly in demand as results from rising sea levels, motorization, and climate change. To endure storm surges and various extreme weather conditions, the coastal defence can be environmentally friendly, protect ecosystems, and provide a positive economic impact on their surrounding areas.

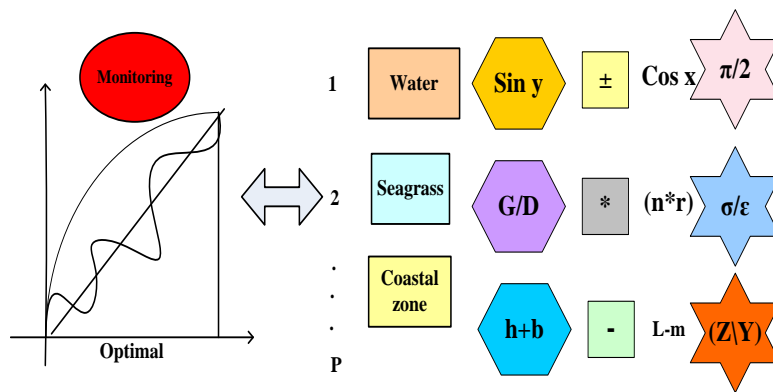


Figure 6. neural networks in commercial fishing to processing stimulation of seagrass:

Figure 6 denotes the commercial fishing sector in the neural network for processing seagrass stimulation.

Figure 6, shown in fish capture, is used to forecast the dispersion of spawning eggs and fish growth biomass and recruitment. Environmental problems and the collapse of the fisheries sector are also big concerns. Tensorial notation is used to describe the data structures. An emphasis is placed on the necessity of switching from a classical to a multi-level hybrid Neural Network paradigm. It has long been recognized that seagrass ecosystems serve as nursery habitats for juvenile fish because they provide safe havens from predators and regions of high quantity of food. The elements that shape fish groups rely heavily on seagrass as a nursery environment are far less well understood. Photosynthesis necessitates exposure to light, and they need to remain near the surface. Anchoring the seagrass to the bottom, its roots provide nourishment.

$$\alpha(k) = \sin \theta - 1 \left(\frac{\sin \alpha}{\cos \alpha}\right) \int \frac{G}{D} \left(\frac{pq}{2}\right) + y dx \rho * \frac{\pi}{2} \iint (h + H) dx = \frac{x^2}{2} + x \iiint \frac{z}{y} + y \tag{12}$$

As shown in equation (12), Seagrass reduction over-enrichment of nutrients, light reduction $\sin \theta - 1$ through the encouragement of high biomass $\left(\frac{\sin \alpha}{\cos \alpha}\right)$ algae overgrowth as epiphytes and $\int \frac{G}{D} \left(\frac{pq}{2}\right)$ macroalgae in shallow coastal $1+ yd xp$ regions and microalgae in deeper coastal waters are naturally postulated. Seagrass habitats at the shore $\frac{\pi}{2} \iint (h + H) dx$ can be harmed by aquaculture, dredging, and $\frac{x^2}{2}$ boat-related activities. The seagrasses, combined with direct human activities and rising sea levels, tropical storms, and $x \iiint \frac{z}{y} + y$ climate change was regarded as a possible threat.

3.4 Convolutional neural network based on fishery management:

Figure 5 denotes the fishery management on the convolutional neural network:

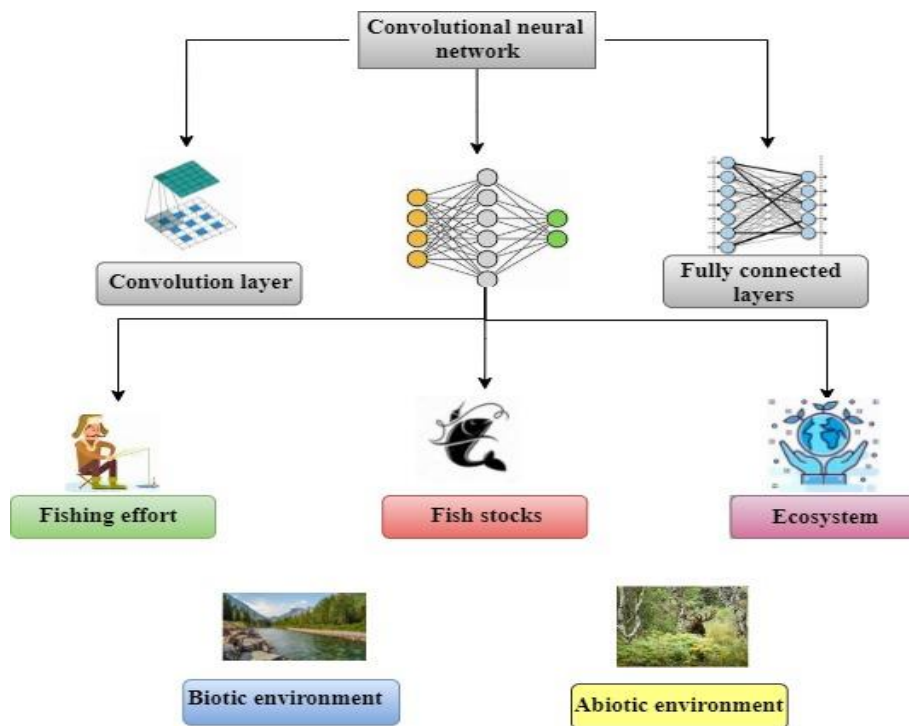


Figure 7. Convolutional neural network in fishing and habitat deterioration:

Figure 7 shows the possibility of recognizing and analyzing images in a convolutional neural network (CNN) that was created with the goal of handling pixel-level input. An essential component of a CNN is a convolutional layer. A collection of filters and settings are taught throughout the course. The quantity of fishing effort is an indicator of fishing. Surrogates are frequently used to describe the mix of inputs required for fishing. The amount of fishing effort is a sign that fishing is going on in the area. The combination of inputs needed for fishing is typically described in surrogates. Neurons in the fully connected layer are feed-forward networks. In an ecosystem, species of all kinds work together to create a life bubble in a specific region of land or water. It is essential to understand that fish stocks are subpopulations of the same species. Fish broth is a foundation for fish soups and sauces created by simmering fish bones with vegetables. An ecosystem's abiotic components and activities collectively refer to the abiotic environment. Abiotic variables, like sunlight, soil water, wind, and humidity, interact with each other and impact living species, including plants and animals.

3.4.1 The derivatives of Convolutional neural network:

$$\alpha(l) = \frac{W \tan \alpha}{H} \left(\frac{3w}{2} + W\right) \cos \theta + \frac{3R\sqrt{3}}{2} \sin \theta \int \frac{1}{\sqrt{n^2-1}} (n + \sqrt{n^2 + 1}) * \sum \frac{y^2}{2\sqrt{n-1}} \tag{13}$$

As shown in equation (13), a neural network with convolutional layers, images $\frac{W \tan \alpha}{H}$ and structured data can be processed by convolutional neural networks (CNN), a type of deep learning neural $\left(\frac{3w}{2} + W\right)$ network. In various visual $\cos \theta$ applications, like the image $\frac{3R\sqrt{3}}{2}$ classification, convolutional neural networks have

established $\sin \theta \int \frac{1}{\sqrt{n^2-1}}$ as the standard of excellence. In $(n + \sqrt{n^2 + 1})$ convolutional neural networks, layers are the primary building $\sum \frac{y^2}{2\sqrt{n-1}}$ components. Filtering an input with a basic convolution leads to activation.

$$\alpha(m) = \tan 2 \left[\frac{x-h-x}{1+x(x+h)} \right] + \left[\frac{h}{1+hx+x^2} \right] * \sum y^2 \sqrt{\frac{\pi}{2}} \left(\frac{dy}{dx} \right) - \left(\frac{d^2y}{dx^2} \right) 2 \cos \left(x + \frac{\alpha}{2} \right) \sin \frac{\alpha}{2} \tag{14}$$

As shown in equation (14), A fishing effort is a good indicator $\tan 2 \left[\frac{x-h-x}{1+x(x+h)} \right]$ of fishing is going on. The number $\left[\frac{h}{1+hx+x^2} \right]$ of hours or days spent $\sum y^2 \sqrt{\frac{\pi}{2}} \left(\frac{dy}{dx} \right)$ fishing, the number of hooks used, the $\left(\frac{d^2y}{dx^2} \right)$ number of meters of nets deployed are all $\cos \left(x + \frac{\alpha}{2} \right)$ common surrogates.

$$\alpha(n) = p\Delta y_0 + \frac{p(p-1)}{1.2} \Delta^2 y_0 \int \frac{y(x+h)-y(x)}{h} + \sqrt{\frac{dy}{dx} = \frac{\delta y}{\delta x}} - \iint \frac{y_3-y^1}{6} \tag{15}$$

As shown in equation (15), an ecosystem's abiotic $p\Delta y_0$ components and processes $\frac{p(p-1)}{1.2}$ encompass anything not alive. Several abiotic $\int \frac{y(x+h)-y(x)}{h}$ variables influence the health $\sqrt{\frac{dy}{dx} = \frac{\delta y}{\delta x}}$ of living species, such as animals and plants, including $\iint \frac{y_3-y^1}{6}$ sunlight, soil, water, wind, and humidity.

Figure 7 Mathematical analysis of convolutional neural network in the growth of seagrass meadows reducing dredging of seagrass:

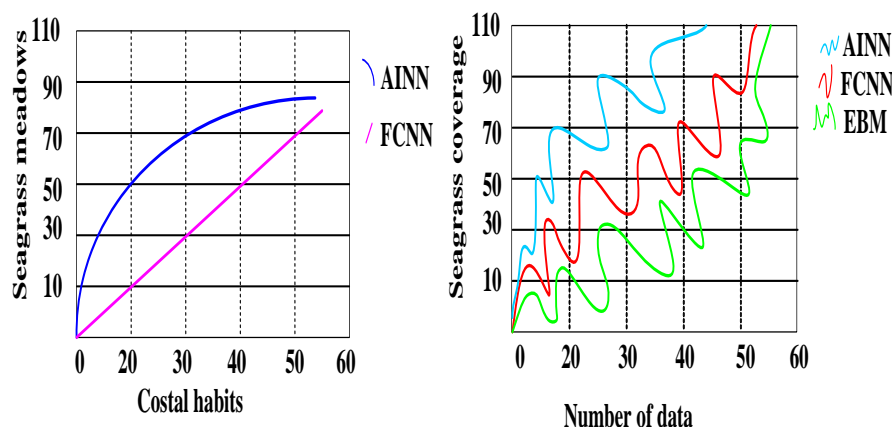


Figure 7. (a) Seagrass meadows inhabit (b) Data seagrass coverage:

Figure 7 denotes the inhabitant of the seagrass meadow and the proportion of the seagrass growth.

Figure 7 Ecosystems dominated by seagrasses are the most prolific and active marine organisms. It serves as nursery grounds and stabilizers of the substrate. As a significant food and habitat for many marine creatures, including fish, octopus and turtles, shrimp, blue crab and oyster, sponge and anemone, and clam, seagrass is an essential part of the marine food web. The seagrass and marine microalgae differ significantly. Seaweed is a multi-cellular alga that lacks circulatory tissues and is not considered a vascular plant. Aerial surveys and remote sensing to acquire large-scale inventory are explored. There are several advantages of permanent transects, and they can identify changes at the smallest possible size. Indicators like biomass, density, and production point to a healthy seagrass meadow. Marine creatures benefit from the food and shelter provided by seagrass. Marine herbivores like the manatee and green sea turtle rely heavily on seagrass as a primary food source. Seagrasses are the main sources, utilizing the sunrays to create organic compounds. Seagrasses use and recycle nutrients from the water column and the sediments in this process.

4. Experimental analysis of neural network model in seagrass applications

Regarding seagrass dispersal, light levels are a critical consideration. Seagrass loss is primarily attributed to lower water clarity and diminished light penetration. Seagrass health can be assessed by measuring the light attenuation coefficient, a key measure that is reflecting much light is absorbed by the water column. Even though linear light

attenuation models are widely utilized in practice, an accurate model is required to include coastal marine environments. The results of the created neural network models are compared with those of linear regression models, model trees, and support vector machines in performance evaluations. The real-time seagrass monitoring based on the parameter of coastal zone management is analyzed from the AINN [38]; the qualitative assessment of seagrass based on the parameter of fishing and a recurrent neural network [39] evaluates habitat deterioration. The modular neural network [40] enhances experimental analysis of risk in coral reef degradation parameter, the parameter of neural network in dredging of seagrass is improved by the convolutional neural network method in the results [41], and the overall performance of monitoring compact of seagrass applications are explained [42].

Table 1: The accuracy of real-time seagrass monitoring increasing coastal zone management:

Number of real-time Seagrasses	PICT	FCNN	EBM	RCAS	BRUV	AINN
5	23.8	18.8	17.5	36.5	57.5	71.2
10	19.2	29.2	31.5	23.5	50.4	66.4
15	22.6	31.6	19.1	38.6	54.5	60.5
20	13.8	23.8	34.3	45.1	59.3	73.2
25	31.9	21.9	30.2	51.9	67.5	72.7
30	26.6	16.6	31.2	53.5	77.6	95.2
35	35.5	37.5	42.8	62.4	75.3	84.4
40	20.7	49.7	37.5	54.3	78.3	92.4
45	57.2	59.2	50.4	62.7	84.6	97.2
50	39.2	49.2	59.2	65.2	72.5	90.4
55	42.3	42.3	58.6	62.3	81.3	93.2
60	43.3	46.4	59.6	63.4	78.6	90.5
65	53.3	46.3	53.2	67.4	86.5	97.3
70	48.2	42.5	58.4	63.5	69.2	92.2
75	19.8	26.5	21.7	59.6	51.6	80.2
80	21.9	22.6	31.9	65.3	73.5	87.6
85	27.3	22.3	29.4	60.7	83.1	89.3
90	32.5	46.3	59.6	63.2	70.7	88.2
95	30.7	53.3	69.3	53.8	69.2	93.4
100	59.2	42.2	58.7	64.9	72.3	93.5

Table 1 says energy generation in coastal areas is encouraged as fuel for power plants can be delivered easily, and cooling water can be disposed of smoothly. As a destination for human settlement and tourism, the landward segment of the coastal zone is quite significant. The important aspects of coastal zones are the interface between land and sea. As the bulk of the earth population resides in these zones, are critical. As the waters and land interact dynamically, in coastal zone management, AINN helps to enhance real-time seagrass monitoring in coastal zone management, promote regenerating seagrasses monitoring, and encourage a neural network model.

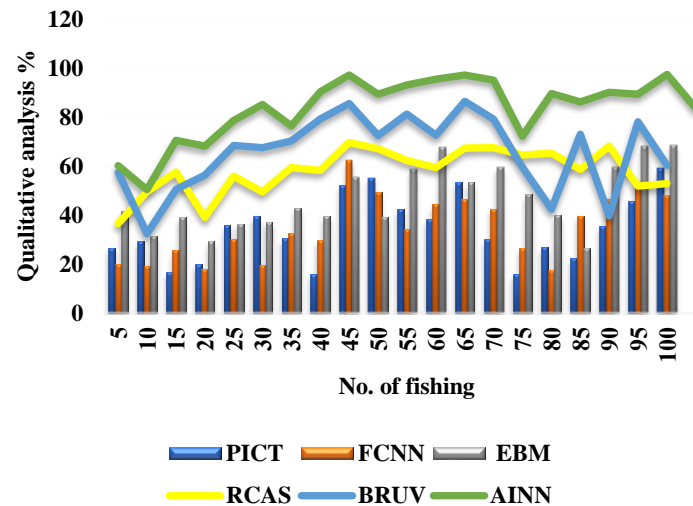


Figure 7. Qualitative assessment of reducing deterioration of fishing and habitat in a seagrass ecosystem:

Figure 7, shows that seagrass populations are mostly at risk from excessive amounts of plant nutrients, a significant source of pollution. Algae blooms, caused by high nitrogen levels, frequently from agricultural and urban waste, obscure the seagrass. Seagrass colonies can be wiped out if there is a drastic reduction in light available, and sedimentation reduces light in the same way. High concentrations of plant nutrients provide the most significant harm to seagrass populations due to pollution. A reduction in light slows seagrass growth and can destroy whole populations. The number of seagrass shoots offers a metric of seagrass abundance over depth gradients and measures seagrass abundance. Shoot density measurements can be connected to water depth, and it is a depth-dependent property. RNN model has been proposed to reduce the fishing and habitat deterioration in the seagrass ecosystem and to analyze the sediment of a seagrass bloom.

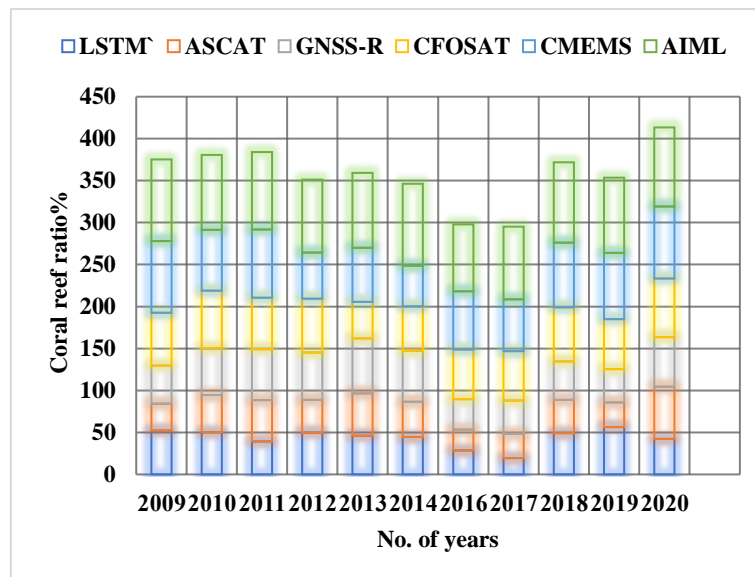


Figure 8. Experimental analysis of Changes in coral reef degradation:

Figure 8, shows coastal development and overexploitation of coral reef resources are some of the most significant factors in coral reef depletion. Due to land development, migration to the beaches has resulted in the degradation of critical coastal habitats, like mangroves and sea grass beds—the sampling and analysis of water components and conditions affected by water quality monitoring. In cleaning up the rivers, monitoring water quality is critical. There is no better way to monitor the health and composition of rivers, streams, and lakes than a stream, river, or Lake Monitor. Effluent discharge monitoring is crucial for approving the discharge of hazardous compounds into surface water and is sometimes applied to coral reef management. MNN in seagrass application improves the qualitative assessment of coral reef deterioration and ensures ecological sustainability.

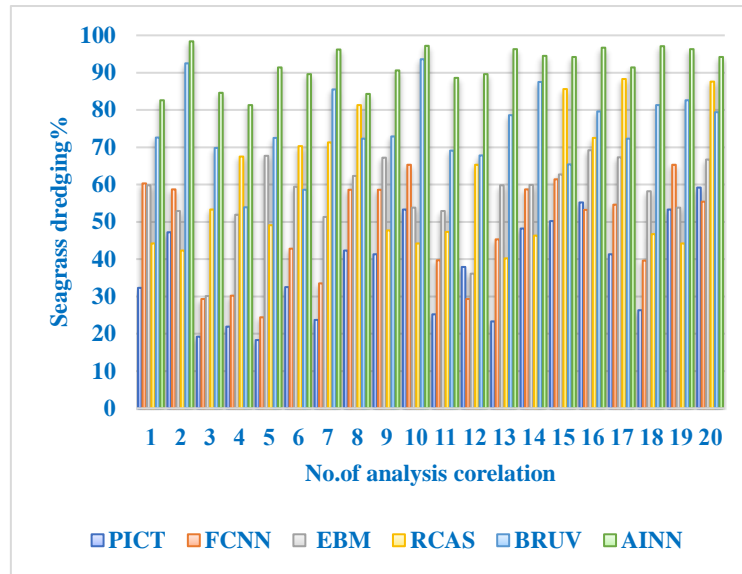


Figure 9. The risk analysis of neural network in dredging of seagrass:

Figure 9, shows dredging can have a significant impact on coastal erosion. Coastal erosion can be enhanced by dredging up sediments from deep channels or trenches that can effectively fill up shallow marshes and wetlands. Seagrass beds are simple to support the spontaneous repopulation in regions, and surface water quality has improved. Seagrass restoration approaches that are proactive include transplanting people from healthy donor beds or seedlings that have been raised in a laboratory. Organic carbon is buried in the water and a significant amount of nitrogen results from this process. Further seagrass beds can achieve climate change mitigation and biodiversity enhancement. CNN model is applied to decrease the risk analysis of neural networks in dredging seagrass and optimize seagrass development, which helps to improve the real-time monitoring of seagrass applications.

Table 2: Overall performance in monitoring and evaluating the seagrass:

	PICT	FCNN	EBM	RCAS	BRUV	AINN
5	32.3	60.3	59.8	44.2	72.6	82.6
10	47.2	58.7	52.9	42.3	92.5	98.4
15	19.2	29.3	30.1	53.3	69.8	84.6
20	21.9	30.2	51.9	67.5	53.9	81.3
25	18.3	24.4	67.7	49.1	72.5	91.4
30	32.5	42.8	59.4	70.3	58.6	89.6
35	23.7	33.5	51.3	71.3	85.5	96.2
40	42.3	58.6	62.3	81.3	72.3	84.3
45	41.3	58.6	67.2	47.7	72.9	90.6
50	53.3	65.3	53.8	44.2	93.6	97.2
55	25.2	39.7	52.9	47.3	69.1	88.6
60	37.9	29.3	36.1	65.3	67.8	89.6

65	23.3	45.3	59.8	40.2	78.6	96.3
70	48.2	58.7	59.9	46.3	87.5	94.5
75	50.2	61.4	62.7	85.6	65.4	94.2
80	55.2	53.2	69.2	72.5	79.6	96.7
85	41.3	54.6	67.3	88.3	72.3	91.4
90	26.3	39.6	58.2	46.7	81.3	97.1
95	53.3	65.3	53.8	44.2	82.6	96.3
100	59.2	55.4	66.7	87.6	79.4	94.2

Table 2 says seagrasses reduce coastal erosion and safeguard homes and communities from the sea's power and sea level rise due to global warming. The seagrasses assist silt delivered by the saltwater collect on the ocean floor by reducing wave energy. Seagrasses minimize coastal erosion and shield places and communities from both the power of the sea and the rise in sea level due to global warming. Enhanced the seagrass growth by reducing bottom wave impact and promoting the accumulation of seawater particles, the overall performance of monitoring and evaluation of seagrass, Coral reef degradation, fishing and habitat deterioration, risk of seagrass dredging, and coastal zone management are better predicted by the proposed model seagrass monitoring application in a neural network model.

5. Conclusion

This study developed a compact real-time neural network model significantly enhanced through Information Technology to monitor seagrass ecosystems effectively. The model, supported by advanced AINN techniques, successfully captures complex environmental relationships and mitigates ecological degradation. By incorporating IT with RNN, MNN, and CNN methods, the model provides an autonomous, efficient, and accurate real-time system capable of assessing seagrass health and carbon capture processes. Consequently, this comprehensive approach ensures improved ecological preservation, habitat restoration, and effective coastal management practices.

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