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An Innovative Approach: Sea Ice Types Classification Using Convolutional Neural Networks with DDDTDWT Filter

Venkata Kondareddy Gajjala, T.J. Naga Lakshmi

Abstract: ***Studying sea ice and its interaction with climate change is crucial due to its significant impact on the environment, society, and global stability. The pressing need to address the underlying reasons for the rapid melting of Arctic and Antarctic sea ice is underscored by its adverse effects on the environment and society. In this proposed study, a Convolutional Neural Network (CNN) is utilized to predict ice types using data from the NSIDC DAAC Advanced Microwave Scanning Radiometer - Earth Observing System Sensor (AMSR-E) collection. This dataset contains parameters such as sea ice types and spans data products from June 2002, obtained from the NASA Data Centre. By employing hand-crafted features as input and a single layer of hidden nodes, the CNN used in this approach generates improved estimates of ice types, outperforming traditional image analysis methods. At each stage, ConvNets use diverse filter banks, feature extraction pooling layers, and fully connected layers with basic activation functions like Relu. This allows the network to build multifaceted hierarchies of features. The sea ice type estimates produced by the CNN are then compared with those obtained from passive microwave brightness temperature data using existing algorithms as well as a proposed CNN algorithm, resulting in an increased classification accuracy of 98.58%. This improvement is particularly notable in the reduction of the error rate, which has been effectively minimized from 3.01% without feature selection to 1.42% with infinite feature selection. When compared to existing algorithms, the CNN demonstrates superior performance. These findings underscore the impact of input patch size, CNN layer count, and input size on the model's performance.***

Keywords: ***Advanced Microwave Scanning Radiometer - Earth Observing System Sensor (AMSR-E), Convolutional Neural Network (CNN).***

I. INTRODUCTION

In the field of operational sea ice analysis, experts use AMSR-E data to create ice charts, which are crucial for providing guidance and support in ice-covered regions. However, manually generating these data analyses is a time-consuming process and can be prone to human errors.

With new satellite missions such as AMSR-E and the European Sentinel mission, we anticipate a significant increase in the volume of satellite imagery. The increasing volume of data poses a challenge in efficiently analyzing and processing imagery. Previous studies have explored automated methods for extracting valuable information from AMSR-E imagery. These studies have used specific features tailored for particular tasks, such as HH autocorrelation, cross-polarization ratio, and scaled polarization difference for estimating sea ice concentration. Over its operational lifespan, AMSR-E data have significantly enhanced our understanding of the seasonal evolution of sea ice, providing important insights into dynamic changes over time. AMSR-E, operating as a passive microwave radiometer, is unaffected by sunlight and certain channels are not impacted by clouds, allowing data collection even in cloudy conditions. Various techniques such as grey-level co-occurrence matrix features, Gabor filters, and Markov random fields have been successfully used to classify AMSR-E imagery into different ice types and ice/water conditions. Generating a robust set of engineered features for automatic information extraction from Synthetic Aperture Radar (SAR) imagery poses a significant challenge. It needs to be adaptable across diverse geographic regions, seasons, and imaging geometries. To comprehensively capture a wide range of ice conditions, it may be necessary to tailor features specific to various locations or seasonal variations. For example, creating a comprehensive database containing HH and HV backscatter values calculated on a region-specific basis, considering factors such as incidence angles and wind speeds could prove to be invaluable. Analysts derive sea ice concentration estimates from AMSR-E images, relying heavily on their nuanced understanding of local sea ice conditions and adept interpretation of visual cues within the images. This complex process involves examining diverse characteristics of AMSR-E images across different scales. Emulating the visual method's capability to synthesize information from various scales and incorporate past knowledge is necessary to carry out this task effectively. CNN has a solid reputation for its ability in feature extraction from images, excelling precisely at considering information across various scales.

In the current research, a CNN is strategically used to assess ice types based on the acquired AMSR-E imagery. This innovative approach not only promises efficiency and accuracy but also aligns with the evolving technological landscape in the field of sea ice analysis.

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II. BACKGROUND WORK

Consider using image feature learning from AMSR-E imagery for ice concentration estimation, which expands upon the feature learning methods used in previous research. This approach has the potential to effectively analyze complex datasets. Deep learning, a type of feature learning, can autonomously interpret complex data visuals at high abstraction levels. In the field of image recognition, deep CNN's are widely used due to their efficiency in modeling local image structures at different scales.

However, there has been limited research on using CNNs to extract features from satellite imagery. Training CNN models requires a large volume of high-quality training data, which can be expensive and impractical to obtain, especially for tasks like ice concentration due to extensive geographical coverage and diverse surface conditions. This challenge is particularly evident in tasks related to ice concentration, as algorithms designed for estimating ice types from passive microwave data may exhibit biases, especially in areas with thin ice and low ice concentration levels. The assessments provided by analysts are generally considered the most reliable and accurate source of ice concentration information. Therefore, the extensive image analysis database available at the NASA Image Data Store can be utilized to explore the application of a CNN for estimating ice types from AMSR-E imagery.

III. PROPOSED WORK ARCHITECTURE-CNN WITH DDDTDWT FILTER

In this study, use the Double Density Dual-Tree Discrete Wavelet Transformation (DDDTDWT) as a technique to remove noise from images of different types of ice. We also apply Grey Level Co-Occurrence Matrices (GLCM) for feature extraction. We select suitable features such as contrast, dissimilarity, energy, entropy, homogeneity, correlation, and variance for classification.

During the process, oriented wavelets are generated using the dual-tree double-density 2-D transformation, and the 2-D input image undergoes a type-tree discrete wavelet transformation. In this transformation, use "fdf" for the first level and "df" for subsequent levels as the analysis filters. The coefficients resulting from the DDDTDWT image filtering are organized. A structured version of the Gray-Level Co-occurrence Matrix (GLCM) is used to derive feature values for each ice type, which are then organized into an array.

As part of the DDDTDWT approach, the results are provided to the convolutional neural networks algorithm, as shown in Figure 1.

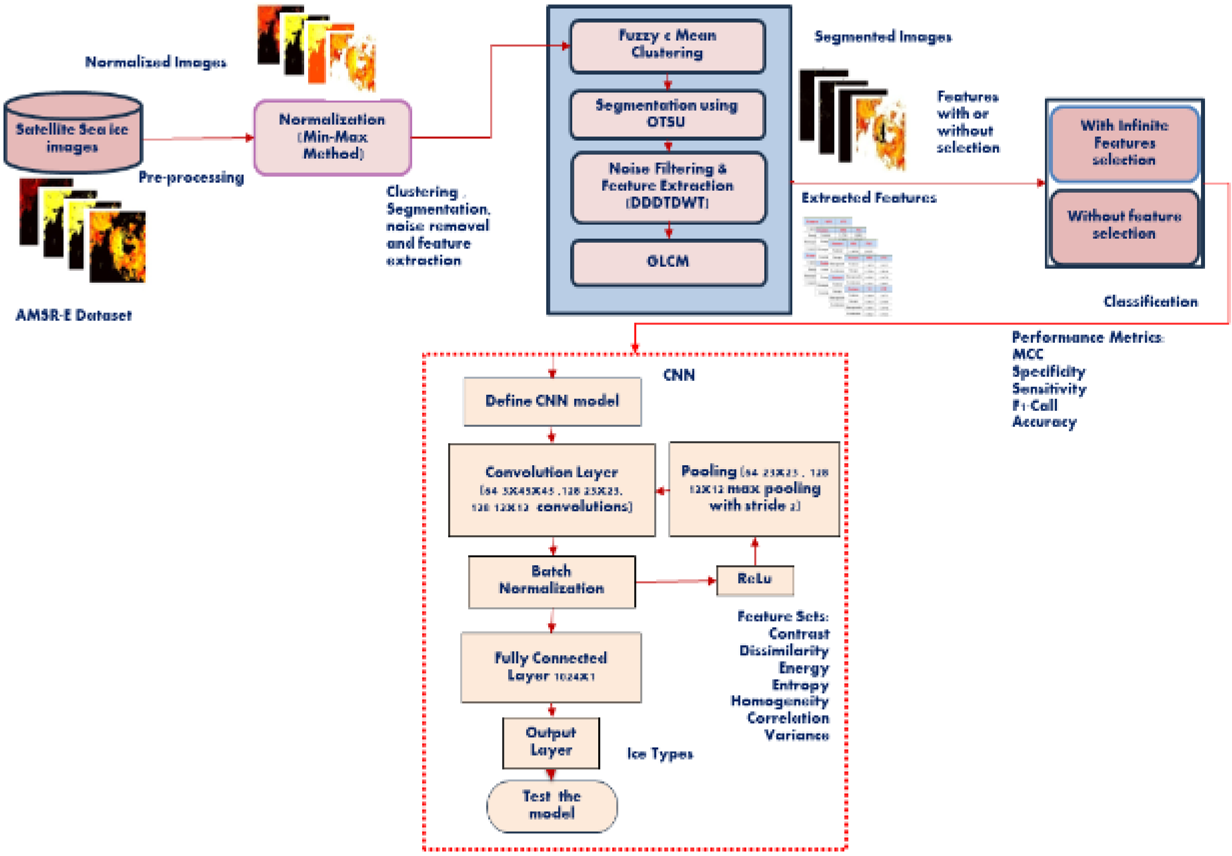

Figure: 1. Proposed Work Architecture-CNN with DDDTDWT Filter

Specifically, the AMSR-E/Aqua Daily L3 12.5 km Sea Ice Concentration, & Snow Depth Polar Grids V003 Level-3 gridded product (AE_SI12) includes brightness temperatures ranging from 18.7 to 89.0 GHz, sea ice concentration, and snow depth over sea ice in dual-pol (HH and HV) Polarizations. These comprehensive datasets contribute to a thorough understanding of the sea ice conditions in the study area over the specified time frame.

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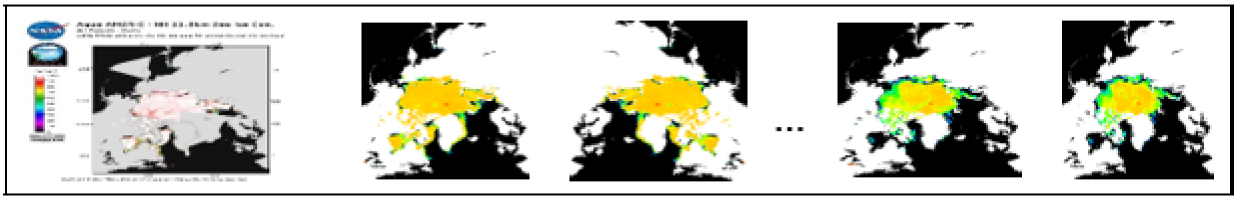

Figure: 2a) Study Area Figure 2b) The dataset for the AMSR-E Level 3 Standard Sea Ice Products

A. Dataset: AMSR-E Imagery

The study area, as illustrated in Figure 2(a) and Figure 2(b), encompasses data spanning a decade from July 2, 2012, to December 14, 2022, utilizing AMSR-E imagery. Throughout the study duration, Sea ice products with AMSR-E Level 3 standard were supplied by the National Snow and Ice Data Center (NSIDC). These products comprise sea ice concentration, generated using the NT2 algorithm, sea ice temperature, and snow depth on sea ice produced from the AMSR-E algorithm.

B. AMSR-E Images Pre-processing

To optimize the management of data volume and reduce image speckle noise, a crucial step is taken with all AMSR-E images, subjecting them to an 8 × 8 block averaging process. Neural networks become more efficient while operating at this reduced scale since it requires a smaller spatial context window. This approach gains favor due to the relatively limited number of available training samples. The sub-sampled images maintain a pixel spacing of one kilometer, with pixel values ranging from 0 to 255. Enhancing CNN performance follows the standard practice of employing input normalization. In this particular investigation, a normalization procedure is applied to the pixel values in the dual-polarized AMSR-E images. This involves computing the mean and standard deviation of pixel values across the complete dataset for each channel. Subsequently, these calculated means are subtracted from each pixel value, followed by division by the respective standard deviation.

When selecting training sample patches in proximity to the land, challenges arise as the CNN may encounter confusion. Land pixels have the potential to misrepresent near by water areas, creating an illusion of ice where there is none. The impact of this issue is contingent on the size of the training patches. In this instance, 45 by 45 pixel patches are utilized, equivalent to approximately 2 kilometers by 2 kilometers on the ground. A straightforward removal of land pixels and setting them to 0 could introduce misinterpretations. Instead of straightforward removal of land pixels a land mask is applied to the AMSR images, replacing land pixels with those resembling either ice or water. This strategic move reduces land interference and, while it may lead to reliance on nearby ice or water pixels for ice concentration determination, tests demonstrate that the land mirroring method effectively mitigates the impact of land on ice concentration and extent estimates. Currently, alternative methods for masking land pixels remain unexplored.

In addition, each pixel's incidence angle in the AMSR image is carefully computed to understand the surface interaction of the signal generated by the radar. These angle values are then transformed into images, ensuring a range of values similar to the AMSR images themselves. Each extracted patch, coupled with the ice concentration and extent located at the patch center from the image analysis, acts as one sample used to train the CNN. In cases where patches exhibit a boundary shape, they are labeled based on the central pixel's shape, although using a label that describes the ice concentration as a mix of both shapes might offer more accuracy. These challenges form the basis for further exploration in future research endeavors.

C. Overview and Configuration of the CNN

A Convolutional Neural Network (CNN) functions as a learning structure with distinct components, each undergoing three crucial steps: convolutional filtering, non-linear transformation, and pooling layers. Usually, a CNN is made up of several of these parts, each of which learns different features of an image. Subsequently, additional layers interconnect these learned features. In this context, a CNN is designed with three filtering layers and two connecting layers, as outlined. The detailed architecture of this CNN is illustrated in Figure1.

Within the convolutional layers, K convolution filters of size $(C_x C_y,\ C_z)$, labeled as C^k, convolve the input matrix (width of S_x pixels, height of $S_y$pixels, and number of channels designated as S_z) representing a patch recovered from the AMSR image. The image patch is subjected to each filter with a stride indicated by P.The outcome of this convolutional operation results in K feature maps, denoted as h^k, each having dimensions $M_x$and M_y as outlined in Equation (1).

$$h^k = (C^k * x) + b \text{ in which}, \text{k} = 1,2 \ldots \text{K} \qquad (1)$$

$$M_x = \frac{S_x - C_x}{P} + 1$$

$$M_y = \frac{S_y - C_y}{P} + 1$$

In this context, the symbol $(*)$ is utilized to illustrate the convolution process. The size of the feature maps $(M_x \times M_y)$ is specified when considering padding in images. Each convolutional layer incorporates filters of varying sizes and quantities, learning the values of these filter weights and a parameter known as bias from the training data.

Every element in the feature maps is subjected to the activation function after the convolution. Here, the Rectified Linear unit (ReLu) activation function is employed, surpassing the older sigmoid function as it accelerates the learning process and yields superior features.

Post the non-linear transformation, the subsequent step is sub-sampling or pooling.

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Max pooling is adopted due to its simplicity and effective performance (LeCun, 2010). Max pooling outputs the maximum value within each pooling window. For instance, with a pooling window size and step size both set to 2, a max-pooling layer produces the maximum value within every non-overlapping two by two window of its input. The convolutional layers are succeeded by fully connected layers, serving as classification modules utilizing features extracted from earlier stages. Each neuron in a fully connected layer is connected to all neurons of its input layer. The initial fully connected layer takes a stack of feature maps (h^k) as inputs. These feature maps, arranged in a flat, linear format, are transformed into the output space using a weight matrix named W and a bias referred to as b. Subsequently, the function f is employed to generate the output.

D. Learning and Assessments

The network is configured for predicting ice types from AMSR-E image patches. Utilizing the loss function, discrepancies between the CNN output and ice types from image analysis are penalized. Following each training session, the loss function is evaluated by computing the loss using the current model on the validation dataset. Commonly used in regression tasks, the loss function quantifies the squared disparity between predicted and actual values, with the objective of minimizing this difference. Here, the training employs backpropagation with a mini-batch stochastic gradient descent (SGD), which will leveraging the derivatives of the loss function. These variations are backpropagated through each pixel in the predictions, updating network elements based on the variations of the loss to the parameters over each mini-batch. Sequential adjustments to the training parameters are implemented, following an epoch-based training approach, where each epoch iterates through all training samples once. Every 20,000 mini-batches, the learning rate is lowered by a factor of 10 in order to improve training efficiency. Training concludes when the loss function's score exhibits minimal change (less than 0.001) for 20 consecutive epochs, preventing early convergence, a common occurrence. A supplemental method called dropout is used to lessen overfitting. A dropout layer stochastically sets neuron outputs in a layer to zero with a predetermined probability. In this case, a dropout layer with a dropout rate of 0.5 is utilized, randomly selecting half of the neurons, forcing the network to acquire more representative features. For experimentation, 500 scenes are randomly divided into 400 learning images, and the remainder for assessment images. Post-training the CNN model, it is applied to estimate ice types for each pixel location in the target AMSR-E images. The CNN model, employing a stride of 1 on input images, advances the input window one pixel at a time during forward propagation.

IV. IMPLEMENTATION AND UTILIZATION

Utilized tools in Python encompass TensorFlow, Geo Pandas, Basemap, and Py Torch. TensorFlow, a comprehensive framework, furnishes extensive tools and resources for the construction and training of neural networks. Complementary to the pandas library, GeoPandas broadens its capabilities to handle geospatial data effectively. Basemap, a toolkit for Matplotlib, facilitates the creation of static, interactive, and publication-quality maps, proving useful for various mapping and visualization tasks. Renowned for its flexibility and dynamic computation graph, PyTorch is employed. In the Python environment, the implementation of AMSR-E image pre-processing and patching leverages the capabilities of these tools. TensorFlow and PyTorch contribute to the construction and training of neural networks, while GeoPandas and Basemap enhance the handling and visualization of geospatial data, offering a robust framework for comprehensive AMSR-E image analysis.

A. Ice Types and its Features

Feature selection is accomplished using the infinite feature selection method. Table 9.1 displays the features with and without selection for various ice types, including multi-year ice (MYI), first-year ice (FYI), young ice (YI), and open water (OW).

In this context, MYI refers to ice that has endured at least one melt season and is typically 2 to 4 meters thick. FYI is ice thicker than 30 centimeters but has not experienced a summer melt season. YI represents ice formed during the current winter season and is less than one year old. OW designates areas without ice coverage.

For C-NN, specific features are identified, such as contrast, dissimilarity, energy, homogeneity, correlation, and variance. Contrast measures intensity differences between neighboring pixels, useful for distinguishing high and low ice concentration or extent. Dissimilarity, a measure of intensity differences, aids in distinguishing ice concentration or extent. Energy, the sum of squared pixel values, gauges overall image brightness related to ice characteristics. Homogeneity, reflecting pixel similarity, helps identify uniform ice areas. Correlation, indicating linear relationships, can uncover patterns in ice characteristics. Variance, measuring pixel value spread, identifies areas of high or low ice concentration. These feature values are then utilized in the next step for selecting desired features.

B. CNN Classification with Infinite Feature Selection and Without Feature Selection by Using DDDTDWT Filter

Now, applies on features derived from the outcomes of the noisy single and double filter using DDDTDWT with GLCM transformation technique by with and without feature selection. With a single filter and double filters through a combination have checked with a selected number of features. After results, changes have been observed with a single filter or double. A limited number of features including contrast, energy, correlation, and homogeneity, are chosen with infinite feature selection method for classification.

In this context of CNN, the features such as contrast, energy, homogeneity, correlation, dissimilarity, entropy, and variance have been selected by Infinite Feature selection method. Here, dissimilarity is a measure of the difference in intensity between neighboring pixels in an array element to distinguish between areas of high and low ice concentration or ice extent. Entropy is a measure of the randomness or disorder in an array element called feature values to identify areas of mixed ice types or concentrations, which would have higher entropy values.

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Variance is a measure of the spread of pixel values in an array element to identify areas of high or low ice concentration or ice extent. These feature values are subsequently utilized in the subsequent step for selecting desired features shown in Table 1 as an example.

Table 1. Features of Ice Types Derived After Filtering by Using DDDTDWT and GLCM with a 4-Bands of a Single Image

Features	MYI	FYI	YI	OW
Contrast	2.0112	2.853	0.2881	2.0269
Dissimilarity	0.3184	0.4298	0.0427	0.3122
Energy	0.8066	0.7625	0.9451	0.4485
Entropy	0.5053	0.6071	0.1542	0.9806
Homogeneity	0.9554	0.9395	0.9943	0.9558
Correlation	0.6780	0.6268	0.8772	0.9167
Variance	5.5241	6.3561	2.5119	32.3216

In the Table 1, Contrast, and Dissimilarity is more in FYI, and less in YI; Energy is more in YI, and less in OW; Entropy is more in OW, and less in YI; Homogeneity is more in YI, and less in FYI; Correlation is more in OW, and less in FYI; Variance is more in OW and less in YI.

C. Selection of Features

Here, have been selected features such as contrast, energy, homogeneity, correlation. The selected features are being done by using infinite feature selection algorithm based on the mean and intensity values of features shown in Table 2.

Table 2. Features of Ice Types by Using Infinite Feature Selection

Features	MYI	FYI	YI	OW
Contrast	2.0112	2.853	0.2881	2.0269
Energy	0.8066	0.7625	0.9451	0.4485
Homogeneity	0.9554	0.9395	0.9943	0.9558
Correlation	0.6780	0.6268	0.8772	0.9167

NOTE: MYI-Multi Year Ice, FYI-First Year Ice, YI- Young Ice OW-Open Wate

D. Performance Metrics for all Ice Types with Infinite Feature Selection and Without Feature Selection

Here, Table 3 displays the results obtained using overall accuracy, error rate, and various metrics like Matthews's correlation coefficient (MCC), sensitivity, specificity, and F1-Score. Matthews's correlation coefficient (MCC) provides a score between -1 and +1, considering true positives, true negatives, false positives, and false negatives. A score of +1 signifies a perfect prediction, 0 indicates a random prediction, and -1 represents the opposite.

Sensitivity, or the true positive rate (TPR), measures the proportion of correctly identified actual positives. In the sea ice context, it evaluates a classification model's ability to accurately identify different ice types. Specificity, or the true negative rate (TNR), assesses the proportion of correctly identified actual negatives. In the sea ice scenario, it gauges a classification model's ability to accurately identify areas without specific ice types. F1-Score, the harmonic mean of precision and recall, considers false positives and false negatives. In the sea ice context, it evaluates the overall accuracy of a classification model in identifying various ice types. Accuracy, the ratio of correctly classified samples to the total number of samples, measures the overall performance of a classification model. In the sea ice scenario, it reflects the model's ability to accurately identify different areas with specific ice types.

Table 3. Performance Metrics of Ice Types with Infinite Feature Selection and Without Feature Selections by Using DDDTDWT and GLCM

Ice Type	Strategy	Mcc	Sensi	Speci	F_1-Score	Acc	Error
MYI	WITH-FS	1	0.999	0.986	0.987	0.993	0.007
	WITH OUT-FS	0.995	0.986	0.986	0.978	0.986	0.013
FYI	WITH-FS	0.998	0.999	0.989	0.979	0.991	0.009
	WITH OUT-FS	0.975	0.972	0.969	0.934	0.962	0.038
YI	WITH-FS	1	0.993	0.945	0.959	0.974	0.026
	WITH OUT-FS	0.989	0.978	0.928	0.989	0.971	0.029
OW	WITH-FS	0.997	0.978	0.976	0.99	0.985	0.015
	WITH OUT-FS	0.925	0.962	0.963	0.989	0.959	0.04

V. RESULTS EXAMINATION

In this context, one critical parameters has been examined, namely sea ice type. This parameter serves as essential in the exploration of sea ice dynamics, climate change, and their profound impacts on both polar and global environments. Extensively employed by researchers and scientists, these parameters provide valuable insights into the state and behavior of sea ice across diverse regions and seasons. Their thorough examination contributes to a deeper understanding of the intricate dynamics governing sea ice, facilitating comprehensive analyses of its responses to environmental changes on a regional and global scale.

A. CNN Classification with Infinite Feature Selection and Without Features by using DDDTDWT Filter

This approach enables the identification of relevant attributes for ice types. Ultimately, the generated performance measures encompass various metrics for each class type, which includes overall accuracy, MCC, sensitivity, specificity, and F_1-score, all achieved through the utilization of classification methodology shown in Table 4.

This methodology facilitates the identification of distinct ice types, including Multi-Year Ice (MYI), First-Year Ice (FYI), Young Ice (YI), and Open Water (OW). Multi-Year Ice (MYI) refers to ice that has endured at least one melt season and is typically 2 to 4 meters (6.6 to 13.1 feet) thick, thickening as additional ice accumulates on its underside. First-Year Ice (FYI) is thicker than 30 centimeters (11.8 inches) but has not survived a summer melt season. Young Ice (YI) forms during the current winter season and is less than one year old, while Open Water (OW) remains uncovered by ice.

Table 4. CNN Classification Performance Metrics of Ice Types with Infinite Feature Selection and Without Features Selection by Using DDDTDWT

Strategy	Mcc	Sensi	Speci	F1 -Score	Acc	Error Rate
With FS	0.9987	0.9922	0.974	0.9787	0.9858	0.0142
Without FS	0.9713	0.9745	0.9615	0.9725	0.9698	0.0301

Note: FS- Feature Selection, SENSI-Sensitivity, SPECI-Specificity, ACC-Accuracy

In the end, the evaluation comprises diverse metrics for each ice type, encompassing overall accuracy, Matthews Correlation Coefficient (MCC), sensitivity, specificity, and F1-score, as determined by the classification methodology outlined in Table 4. As shown in Table 4, The Performance metrics of CNN with infinite feature selection and a remarkable accuracy rate of 98.58 percent are noted across various ice types, as depicted in Figure 3. The error rate stood at 1.42 percent. When comparing results with infinite feature selection and without feature selection, utilizing the de-noising filter DDDTCWT and GLCM transformation technique, the CNN classifier demonstrated improved accuracy by 0.48 percent with M-SVM [35].

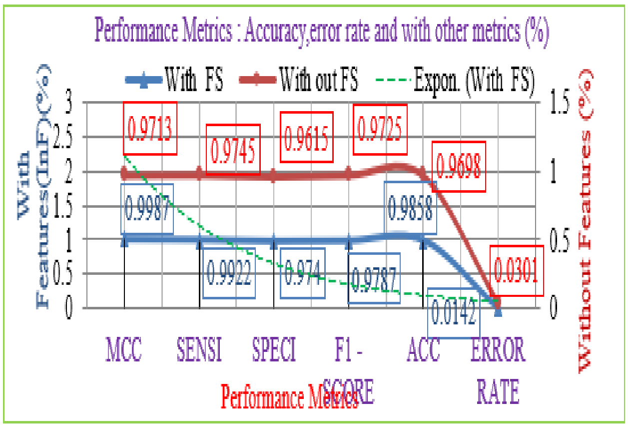

Figure 3. Illustrates the Evaluation Outcomes with Infinite Feature Selection and Without Feature Selection by using DDDTDWT Filter. Note: FS-Feature Selection, SENSI-Sensitivity, SPECI-Specificity, ACC-Accuracy

In a summary, accuracy rate of 98.58 percent was observed across ice types, accompanied, as demonstrated in Figure 3 with infinite feature selection by an error rate of 1.42%, and without feature selection by an error rate of 3.01 percent through the utilization of the de-noising filter DDDTDWT and GLCM transformation technique, the accuracy of the CNN classifier is enhanced 1.59 percent. Furthermore, there is a significant improvement in other performance parameters, including MCC at 99.87% sensitivity at 99.22%, specificity at 97.4%, and F_1-score at 97.87% with infinite feature selection.

B. Comparisons Between Proposed CNN with Existing Algorithms with Infinite Feature Selection and Without Feature Selection Using DDDTDWT Filter

The comparison of CNN with existing algorithms infinite feature selection and without feature selection by using DDDTDWT Filter, Note: FS- Feature selection shown in the Table 5.

Table 5. Comparison of Proposed Method on Accuracy and Error rate with Existing Algorithms with Infinite Feature Selection by using DDDTDWT

S. No	Method	Accuracy	Error Rate
1	Proposed CNN by using DDDTDWT	98.58%	1.42%
2	Wang, Lei, et. al.[31] by using RF	96.20%	4.80 %
3	Wang, Lei, et. al. [32] by using NN	89.10%	10.80%
4	Giorgio Roffo, et. al. by using Feature Selection	94.60%	5.40%

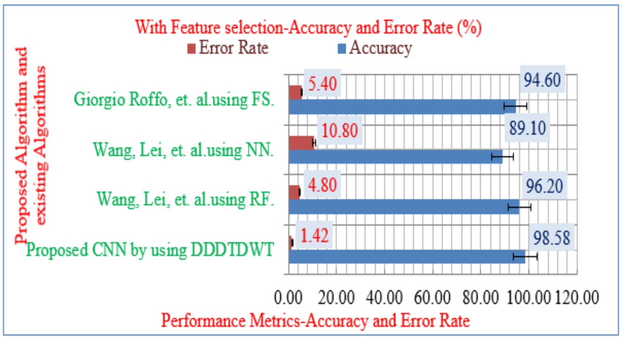

Figure 4. Comparison of all Proposed Methods on Accuracy and Error Rate with Existing Algorithms with Infinite Feature Selection by Using DDDTDWT Filter

In accordance with Chai, Hum Y. et al., Giorgio Roffo et al., and Wang et al., various approaches have been employed to enhance classification accuracy. For instance, the utilization of GLCM has yielded improvements, and feature selection techniques have been applied as well. Furthermore, the combination of RF and NN has been explored to achieve favorable outcomes. Notably, through the implementation of the C-NN algorithm, an enhancement in classification accuracy of 98.58%, as decorated in the graphical representation presented in Figure 4. This improvement is especially evident in the reduction of the error rate, which has been effectively 1.42% through the CNN with infinite feature selection using DDDTDWT.

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Table 6. Comparison of all Proposed Methods on Accuracy and Error Rate with Existing Algorithms Without Feature Selection by Using DDDTDWT

S. No	Method	Accuracy	Error Rate
1	Proposed CNN by using DDDTDWT	96.98%	3.01%
2	Wang, Lei, et. al. [31] by using RF.	96.20%	4.80 %
3	Wang, Lei, et. al. [31] by using NN.	89.10%	10.80%
4	Giorgio Roffo, et. al. by using FS.	94.60%	5.40%

In accordance with Chai, Hum Y. et al., Giorgio Roffo et al., and Wang et al., various approaches have been employed to enhance classification accuracy shown in Table 6. For instance, the utilization of GLCM has yielded improvements, and feature selection techniques have been applied as well.

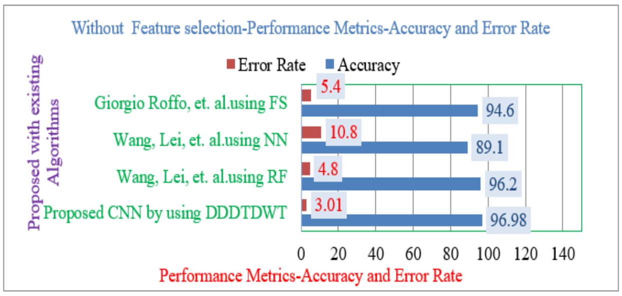

Figure 5. Comparison of All Proposed Methods on Accuracy and Error rate with existing algorithms Without Feature Selection by Using DDDTDWT Filter

Furthermore, the combination of RF and NN has been explored to achieve favorable outcomes. Notably, through the implementation of the C-NN algorithm, an enhancement in classification accuracy of 96.98%, as decorated in the graphical representation presented in Figure 5. This improvement is especially evident in the reduction of the error rate, which has been effectively 3.01% through the CNN without feature selection using DDDTDWT.

VI. CONCLUSIONS AND FUTURE ENHANCEMENTS

In the exploration of ice types, an innovative system was developed to identify various ice types within a sea ice block by analysing satellite sea ice images. In an exploration, with infinite feature selection using DDDTDWT, utilization of GLCM has yielded improvements. Furthermore, the combination of RF and NN has been explored to achieve favorable outcomes. Notably, through the implementation of the CNN algorithm, an enhancement in classification accuracy of 98.58%. This improvement is especially evident in the reduction of the error rate, which has been effectively minimized from 3.01% (without feature selection) to 1.42% through the CNN algorithm.

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Availability of Data and Material	Not relevant.
Authors Contributions	All authors have equal participation in this article.

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