Prediction of Ozone Depletion Levels using Intelligent CNN-SVM Classification System

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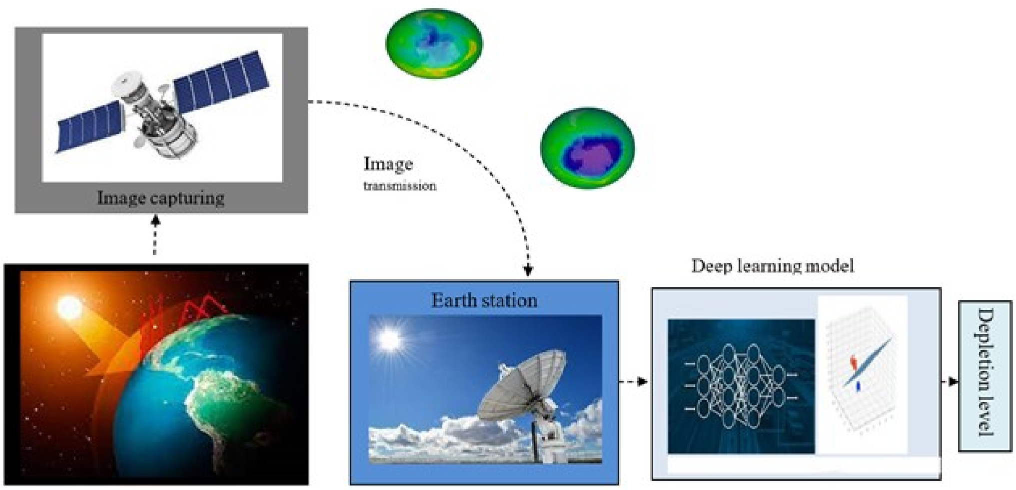
GRAPHICAL ABSTRACT



ABSTRACT

The concentration of ozone in the earth atmosphere has been steadily falling by 4% in the total amount since late 1970. With the widespread usage of modern industry chlorofluorocarbons, the rate at which ozone content decreases is escalating, resulting in an ozone hole. The depletion permits harmful UV into the earth surface which brings harmful hazards to earth living organisms. Increased UV radiation exposure can lead to skin cancer, cataracts, and ecological disruptions. The machine learning models face difficulties in accurately accounting for unpredictable events, such as sudden changes in emission patterns or unforeseen interactions, which limits their capacity to provide precise and reliable forecasts for future ozone depletion scenarios. To overcome this issue, a novel hybridization of Convolution Neural Network (CNN) and Support Vector Machine (SVM) is proposed to detect the variation in the ozone depletion around earth surfaces. The input images are collected from the thermosphere meteorological satellite and transformed into clean data in preprocessing. Then, the images are annotated and fed to the learning model for training. Followed by SVM classifier taken the CNN feature as an input and show the exact level of the ozone. The experimental findings show that the proposed CNN-SVM framework accomplishes satisfactory prediction accuracy of 99.44%. The overall accuracy range improves by 0.21%, 6.74%, and 4.44% with the CNN, SVM-IF, and Faster RCNN test outcomes, and by 2.59%, 3.52%, and 4.13% with the proposed CNN model, respectively. The proposed SVM model increases the total f1-Score by 2.3%, 3.19%, and 0.7%, respectively. The proposed CNN-SVM model obtains high accuracy rate than other existing models.

Keywords: Convolution Neural Network, Support Vector Machine, Ozone Depletion, Intelligent System

1. Introduction

The ozone layer is generally found between 15 and 35 kilometers above the surface of the planet, with a concentration of 0.3 per million air molecules. The ozone layer acts as a filter, absorbing solar radiation that hits the planet. While some of the sun's radiation is necessary for life, too much of it can be detrimental to humans and other living organisms. Ozone traps 97-99 percent of the devastating UV (ultraviolet radiation) light (Hogeveen 2021), which can pass through organisms' protective layers, such as skin and destroying DNA in animals and plants (McElroy and Fogal 2008a).

The ozone layer could absorb most of the UV-B (280-315nm) and UV-C (100-280mm) which are severely harm the people health (Björn 1996; Neale et al. 2021b).

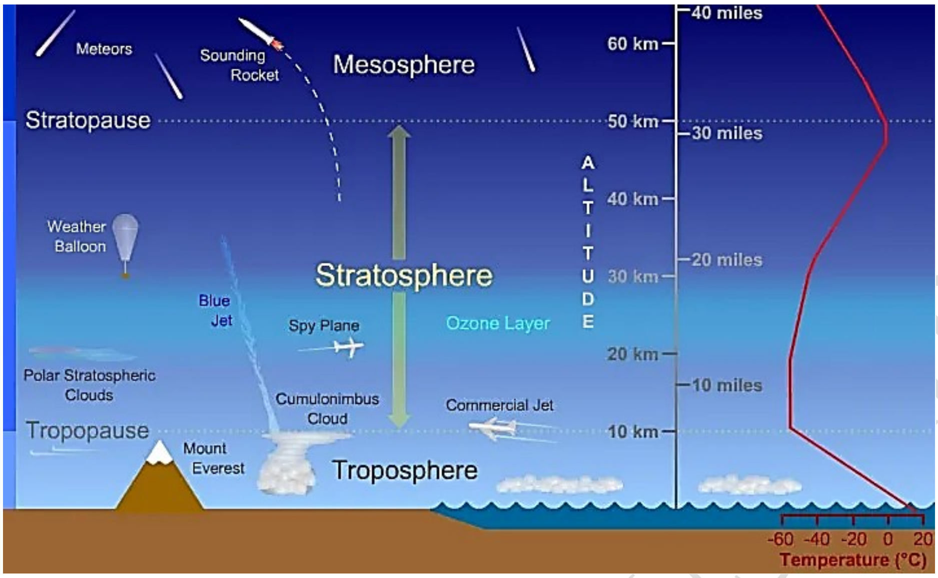


Figure 1. stratosphere ozone Function

The phrase ozone depletion describes the decrease in ozone molecule concentration in the globe's stratosphere, especially in the protective ozone layer. This layer is essential for keeping life on Earth safe because it absorbs most of the sun's damaging ultraviolet (UV) rays. Ozone-depleting substances (ODS), which are compounds produced by humans and include methyl chloroform, carbon tetrachloride, halons, and chlorofluorocarbons (CFCs), are the main causes of ozone depletion. The issue of ozone depletion gained widespread attention in the late 20th century when scientists developed the formation of the Antarctic ozone hole. This hole, characterized by a significant reduction in ozone concentration over Antarctica, raised global concerns about the potential adverse effects on human health, ecosystems, and climate.

The prediction of ozone depletion levels has become an increasingly complex and crucial task, prompting the integration of deep learning techniques to enhance our understanding and forecasting capabilities. The Prediction of Ozone Depletion Levels using deep learning presents a multifaceted problem that necessitates innovative solutions to address the intricacies of atmospheric processes, chemical interactions, and climate dynamics. While deep learning holds great potential for enhancing predictive capabilities, several challenges impede the development of robust models for accurate and reliable ozone depletion forecasts. Atmospheric and chemical data related to ozone depletion are inherently complex, involving various interacting variables and dynamic spatial-temporal patterns. Ensuring the availability of comprehensive, high-quality datasets is a challenge. Ozone depletion has far-reaching consequences, posing risks to human health, ecosystems, and wildlife. Increased UV radiation exposure can lead to skin cancer, cataracts, and ecological disruptions. The impact of climate change on ozone depletion is a complex and evolving factor. Changing temperature and atmospheric circulation patterns can influence the distribution of ozone-depleting substances and alter the dynamics of ozone chemistry.

Addressing these challenges requires interdisciplinary collaboration between atmospheric scientists, climate experts, and deep learning researchers. The development of advanced models, data harmonization techniques, and methods to enhance interpretability are essential to unlock the full potential of deep learning in predicting ozone depletion levels, ultimately contributing to effective environmental management and policy formulation. The key contribution of the following models are as follows.

- The main goal of the proposed intelligent system is to predict the depletion level precisely with less complexity and storage. To achieve this hybridization of CNN and SVM is proposed.
- Firstly, the images are collected from the thermosphere meteorological satellite and transformed into clean data in preprocessing.
- Then, the images are annotated and fed to the learning model for training. Followed by SVM classifier taken the CNN feature as an input and show the exact level of the ozone.

The remainder of the document is structured as follows: A overview of several recent studies on ozone depletion detection can be found in Section 2. Section 3 offers a thorough explanation of the recommended approach. In Section 4, the results of the proposed model are examined and contrasted. Section 5 explains our conclusion and the future scope.

2. Related studies

To classify ozone depletion, numerous machine learning and deep learning techniques have been created. Some existing tactics and limits are briefly discussed in this section.

In (Zhu et al. 2020) had recognized a new deep learning approach to predict the ozone depletion over the Antarctica region. Training photos were acquired from a meteorological satellite and each one was assigned a label. Learning model CNN is exploited for ozone fluctuation detection. It achieved prediction accuracy of 99.23% yet complexity level is high.

In (Sayeed et al. 2020) had implemented DCNN network to detect concentrations on 2017. Data of air pollution and meteorological were obtained between 2014 and 2017 to train the model. This model had a track record of accurately predicting ozone concentrations 24 hours ahead of time.

In (Hoshyaripour et al. 2016) introduced a predication model to monitor ground ozone level. FS-ANN deep learning model was applied to predict the dense level of ozone from air quality images. Implementation cost and complexity of this model is relatively low yet prediction result is not sufficient.

In (Divya et al. 2014) had introduced an image processing technique to detect ozone layer depletion. Firstly, Satellite images were process with K means clustering then fed to the computation of PH value. However, detection performance was tampered when handling the complex data.

In (Eslami et al. 2020) had established a prediction system with CNN for real time ozone monitoring with parameters such as RH, rain, Nox, ozone etc. This model achieved good forecasting performance with less minute for collected image. Any how this method not achieve favorable result for real time detection.

In (Sayeed et al. 2021) had developed a hybrid approach to predict the concentration level of the ozone in early stage. CMAQ-CNN model trained with air pollutant images and had obtained predicted result before 24 to 48 h. complexity memory requirements were the road blocks of this technique.

In (Nowack et al. 2018) had developed a machine learning strategy to analyze temperature changes to detect ozone-based climate changes. In this method measurements were taken and given to the linear regression model to predict the climate variation. This model struggled to detect when non linearity emerges.

In (Chauhan and Vamsi 2019) had established an ozone measurement system from air quality data. Herein unsupervised algorithms SVM and IF had selected to predict the ozone. IF method was achieved detection accuracy of 92.7% yet this tolerance level is low to complex data [24]

In (Aslam et al. 2021) had introduced F_RCNN model to predict the depletion part of the ozone. 1000 images were collected to train the model. This model had achieved the accuracy of 95 to 93%. However, this model required high memory and computation time [25]

Aforementioned techniques have the limitation of low accuracy, memory requirement, and computation complexity. To solve the constraint CNN-SVM based intelligent system is proposed in this study.

3. Proposed method

The main goal of the proposed intelligent system is to predict the depletion level precisely with less complexity and storage. To achieve that hybridization of CNN and SVM is proposed. Firstly, the images are collected from the thermosphere meteorological satellite and transformed into clean data in preprocessing. Further the images are annotated and fed to the learning model for training. Followed by SVM classifier taken the CNN feature as an input and show the exact level of the ozone. The conceptual diagram of the proposed model is shown in fig 2

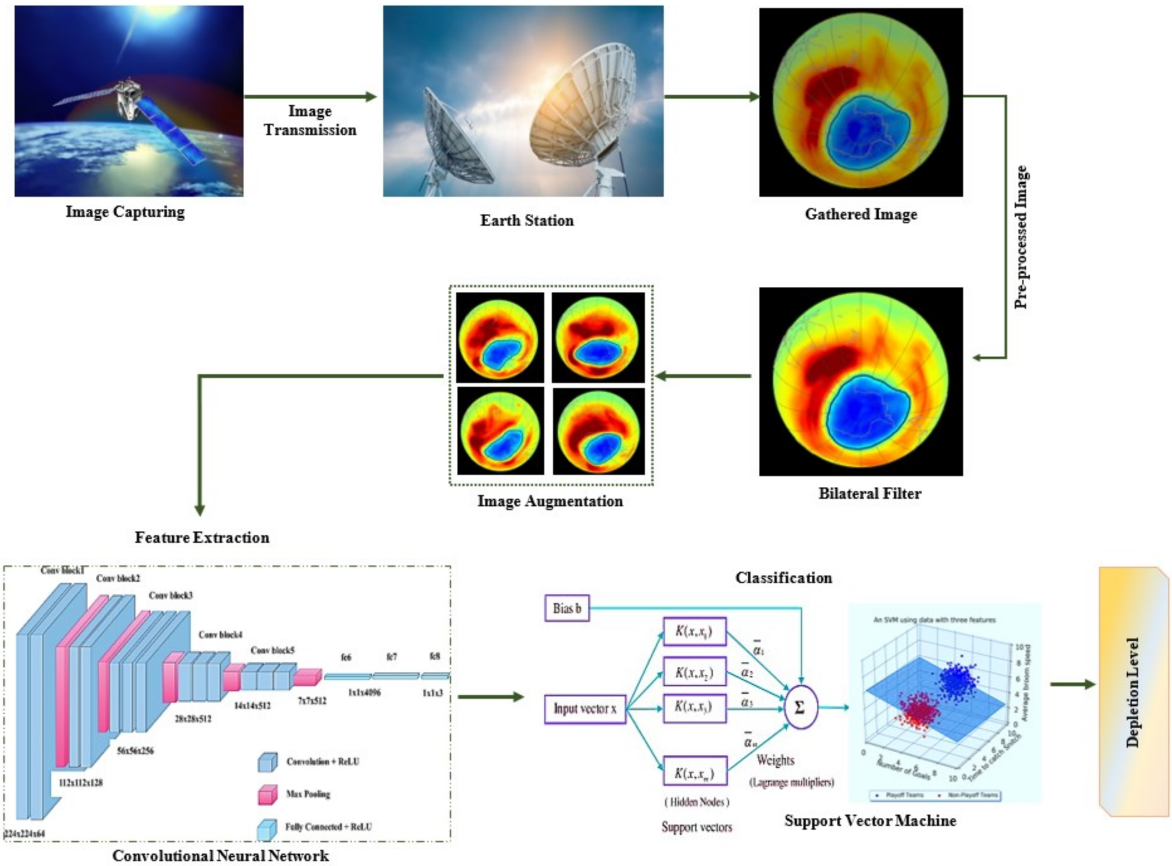


Figure 2. Schematic Illustration of the proposed methodology

3.1. Image acquisition

The ozone depletion images utilized in this study were taken from a meteorological satellite between 2015 and 2020. There are 1472 normal images and 3088 depletion fluctuation images in the data set. Images have a 256x256 pixel resolution and a 24-bit format. A meteorological satellite is a type of satellite designed and equipped to monitor and collect data related to the Earth's atmosphere and weather conditions. These satellites play a crucial role in modern meteorology by providing valuable information for weather forecasting, climate monitoring, and environmental research. The collected data are implemented to the CNN network to detect the depletion level features. The feature extraction model images were annotated for training purposes.

3.2. Data Preprocessing filter

To improve their comprehension for subsequent processing, the gathered images are structured and enhanced in this phase using a bilateral filter. For the purpose of fitting the learning module, the image size is shrunk to 224 x 224. A median filter is executed initially to remove impulse noise in order to address the problem of noise-corrupted pixels in images that are causing fault detection. In order to prevent additional noise, wiener filters are used afterwards.

Median filter:

A median filter is a non-linear digital signal processing technique commonly used for smoothing or reducing noise in an image or a signal. Whereas a median filter substitutes the median value of each nearby pixel for each pixel's value, a mean filter swaps the value of every pixel with the average weighted of its surrounding pixels.

wiener filter:

The Wiener filter is a powerful signal processing technique used for the restoration of signals and images corrupted by noise. The Wiener filter operates in the frequency domain, utilizing the power spectral density of the original signal and the noise to estimate a transfer function that minimizes the mean square error in true signals. This filter provides an optimal trade-off in noise reduction and preservation of signal details, making it widely used in various fields, including telecommunications, audio processing, and medical imaging.

3.3 Data augmentation:

To increase the generalization ability and eliminate the over fitting of the proposed model purpose images are augmented with rotation, brightness enhancement, flipping and scaling operations. From augmentation technique 1000 images were obtained. Data enhancement is an algorithm for learning that applies several changes to collected data samples in order to artificially expand the size and diversity of a dataset. Data augmentation applies adjustments to the model, such as flips, rotations, scaling, cropping, or adjustments to brightness and contrast, to improve the model's performance on previously unknown data and increase its capacity to generalize. This method is particularly useful when the available dataset is limited, as it mitigates the risk of overfitting by exposing the model to a broader range of input variations. Data augmentation is commonly applied in image classification, natural language processing, and other domains to improve the robustness and performance of machine learning models.

3.4. CNN-SVM learning model

CNNs are extensively used for feature extraction as well as categorization. Whereas this method can produce satisfactory results, it usually entails intricate networks that require a lot of storage when used on huge datasets. As a solution, a unique architecture is being developed to address these constraints. SVMs can outperform traditional neural networks when it comes to classification. In this work, a CNN feature extractor and an SVM are coupled. In this conceptual scheme, the CNN's hidden layers are persisted after training, and the features acquired by the CNN are then supplied into the SVM, which is subsequently trained as a classifier, as illustrated in Fig. 4.

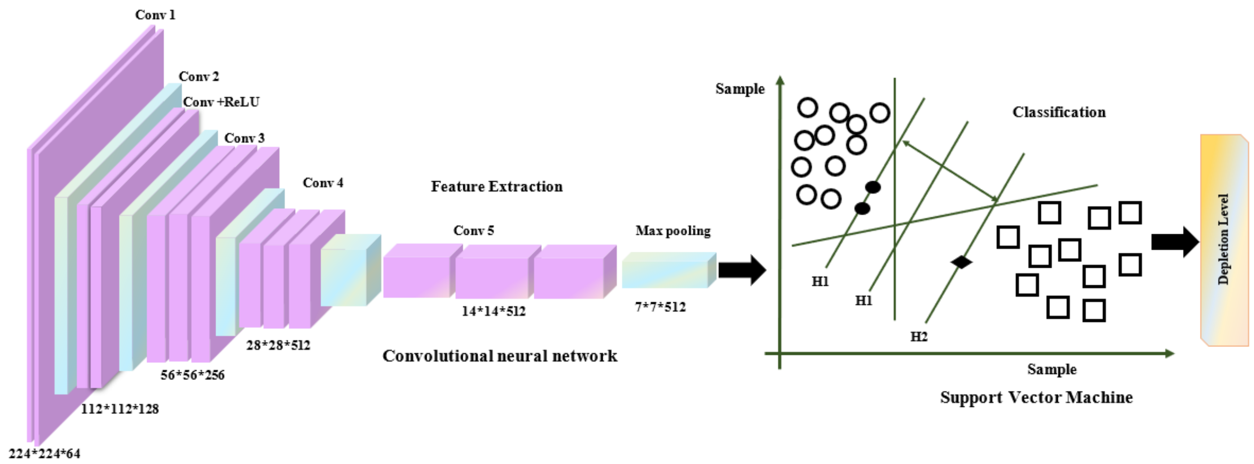


Figure 3. Architecture of proposed CNN-SVM model

3.5. Feature Extraction

A Convolutional Neural Network (CNN) consists of multiple layers designed to efficiently process and extract hierarchical features from input data, commonly used in tasks like image recognition. The input layer, representing the raw data, such as an image. The subsequent layers typically include convolutional layers responsible for detecting patterns and features using filters, pooling layers to reduce spatial dimensions and computational cost, and activation functions like

ReLU to introduce non-linearity. Convolutional and pooling layers are often stacked to form deeper representations. Fully connected phase is combine these features for final predictions. The final layer, usually a softmax layer, outputs the probability distribution over different classes.

In the proposed system Resnet-101 has been employed as a deep learning model, which is efficiently limiting the decline issue with the Identity link. The ResNet (Residual Network) architecture is known for its deep structure, mitigating the vanishing gradient problem through the use of residual blocks. ResNet consists of several layers organized into blocks. Each block contains residual connections, allowing the model to learn the difference between the current layer's features and the features of the input to that block. A stack of layer convolutions forms the first neural block, which followed by reduced linear unit (ReLU) activations and batches of normalization. This block extracts basic low-level features from the input data. The fully connected layer with softmax activation, generates the output probabilities for different classes based on the extracted features.

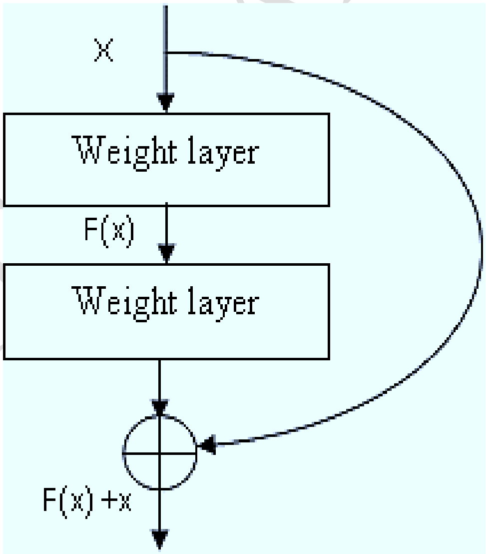


Figure 4. Res Net Shortcut Connection in the Convolutional Neural Network

Unlike other learning model, nonlinear stacked layers of Resnet-101are hoped into the residual map $(f(z) = h(z) - z)$ instead of $h(z)$. Consequently, the performance can be enhanced overall if the model is able to learn the distinction between input and output. Identity mapping is carried out via the Resent shortcut connection, and the outputs of this process are combined with the results of the layered levels. There are no new parameters added, and the complexity level remains unchanged by incorporating the identity connection. The short cut link in the suggested model skips two layers. Finding the perfect layout in an equal map is quite simple compared to traditional mapping.

The Resnet-101 shortcut connection is shown in Figure 5. The distinctive map of the given layer is shown by equation (1).

$$Y = F(z\{W_i\}) + z \tag{1}$$

$F(z\{W_i\})$ Represent the residual map. $F = W_2\sigma(W_1 z)$ Where σ is the activation function (Relu).

Table 1. Resnet-101 layer representation

Layer name	units	Output size
Conv_1	7×7, 64, stride 2	112×112
Conv_2	3×3 max pool, stride2	56×56
	$\begin{pmatrix}1\times 1\\ 3\times 3\\ 1\times 1\end{pmatrix}$×3	
Conv_3	$\begin{pmatrix}1\times 1\\ 3\times 3\\ 1\times 1\end{pmatrix}$×4	28×28
Conv_4	$\begin{pmatrix}1\times 1\\ 3\times 3\\ 1\times 1\end{pmatrix}$×23	14×14
Conv_5	$\begin{pmatrix}1\times 1\\ 3\times 3\\ 1\times 1\end{pmatrix}$×3	7×7
Average pool, SVM		

$F + z$ operation is performed by short cut connection. $\sigma(y)$ is adopted for non linearity after addition. The main benefit of Resnet-101 is the shortest link does not increase the number of parameters or computational complexity. a table 1. summarizes the Resnet-101dimension reduction representation of each layer.

For training Resnet-101 learning rate is initially set as 0.001, ReLU is act as an activation function. Make the model into optimal structure SGD optimization is applied. After the training SVM model is replace instead of FC layer as a classifier.

3.3. SVM classifier

SVM is a machine learning approach, with several kernel functions that can transform nonlinear indistinguishable problems to linear solvable problems. Support Vector Machines (SVMs) can be a valuable tool for ozone depletion level prediction, particularly when dealing with classification problems. Support Vector Machines (SVMs) are a class of supervised algorithms that excel in both classification and regression tasks. Unlike neural networks, SVMs do not have layers in the traditional sense, as they consist of a single layer responsible for decision-making. The input layer in the SVM context represents the feature vector of a data point. Each feature corresponds to a dimension in the input space. The SVM implicitly transforms the input features into a higher-dimensional space through a process called the kernel trick. This transformation allows the SVM to find a hyperplane that separates the data points more effectively, even when the original feature space is not linearly separable. The analogy between points of data in the higher-dimensional region is efficiently captured by the kernel function, which determines a dot product for the converted feature vectors. Polynomial, radial basis function (RBF), and linear kernels are examples of common kernel functions.

The data points that are nearest to the choice boundary (hyperplane) are known as support vectors. They play a crucial role in determining the optimal hyperplane and are the primary contributors to the decision function. Based on the sign of the decision function, the SVM classifies the input data point into one of the predefined classes. The decision is made by comparing the computed decision value to a threshold. The CNN feature output data S(x) is projected into the feature space and then optimal separate hyper plane is determined for predict the ozone level. Support Vector Machines combine the flexible margin and kernels trick to determine the best boundary for linearly non-separable instances. The input data S(x) is defined as follows:

$$S(x) = \{(\vec{u}_l, v_i) | (\vec{u}_l, v_i) \in R^m \times R, l = [1,577]\} \quad (2)$$

Whereas $v_i \in \{1,2,3,4,5,6,7,8\}$ (all number denotes which of the groups it corresponds to), I = [1,864]. To detect the optimal margin hyper plane, SVM soft margin linearly segregate the data S.

Minimize: $$Q(\vec{W}, b, \vec{\zeta}) = \frac{1}{2}\vec{W}^T . \vec{W} + C \sum_{i=1}^{l} \zeta_{i,} \quad (3)$$

Subject to $\begin{cases} y_i(\overrightarrow{W}^T\ \emptyset(\vec{u}_l)b) \geq 1 - \zeta_i \\ \zeta_i \geq 0, i = 1,..,l \end{cases}$

Where $\overrightarrow{W}$, depicts the vector dimension of m, b represents the scalar, slack variables are ζ_i, penalty parameter C helps to reduce the classification error through elaborate the margin. To the function of $\emptyset(.)$ mapped the training data into the maximal dimension. To use a Lagrangian framework, the remedy to the fundamental optimization issue is usually calculated by solving its dual problem.

Minimize $D(\overrightarrow{\alpha}) = -\sum_{i=1}^{l} \alpha_i + \frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l} v_i v_j\ \alpha_i \alpha_j k(\vec{u}_l, \vec{u}_j)$, (4)

Subject to $\begin{cases} \sum_{i=1}^{l} v_i\ \alpha_i = 0 \\ 0 \leq \alpha_i \leq C, i = 1,..,l \end{cases}$

$\alpha_i(i = 1,..,l)$ is denote the positive multiplier of Lagrangian, $k(\vec{u}_l, \vec{u}_j)$ is a kernal function which done the kernel trick through estimates the dot-product for the input data in the feature space, without finishing the explicit map $\emptyset(.)$. The decision of the ozone depletion level function is

$$g(\vec{u}) = sin\{\sum_{\vec{x_l} \in V_s} \alpha_i y_i K(\overrightarrow{u_l}, \vec{u}) + b\} \tag{5}$$

Here $\overrightarrow{u_l}$ is the support vector (sv_s). To control the RBF kernel, gamma value is set as 0.0001<gamma<10 and penalty parameter(C) is set as 0.1<C<10e to exactly fit the input data into high dimensional plane. Finally, the depletion level of ozone layer is accurately predicted using the proposed CNN-SVM frame work.

4. Result and discussion

This section examines and compares the proposed CNN-SVM framework's performance to various currently used techniques.

4.1. Experimental Results

In the proposed model, CNN is first trained with images and SVM is implemented to improve prediction and reduce time complexity, computation storage. The CNN-SVM predicted ozone depletion level in 2020 dec 1-15 days is shown in Fig 5. The outcome is then compared to the manual projected result as well as other cutting-edge models. Comparison to the other techniques, CNN-SVM closely matches the ground truth result.

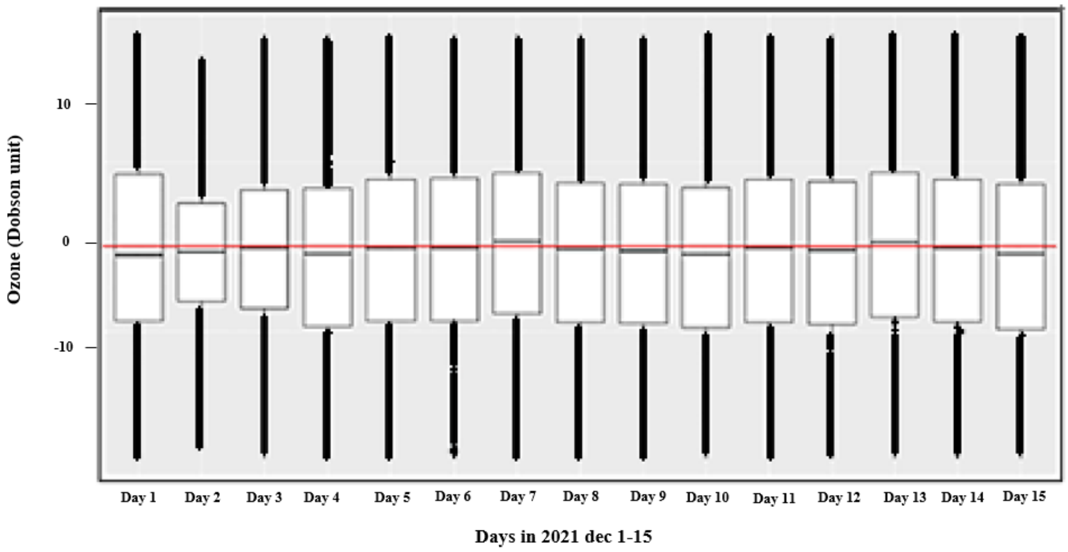


Figure 5. Experimental outcomes of the depletion fluctuation prediction in 2020 dec (1-15) days

Fig 6 shows the global level depletion prediction plot of CNN-SVM between the year of 1980 and 2020.The result is predicted without solar effect dataset. During 1980 and 1990, worldwide ozone levels dropped on average every year. After 1991, attributed to the impact of volcano aerosol from the Mt. Pinatubo explosion, the depletion exacerbated for several year.

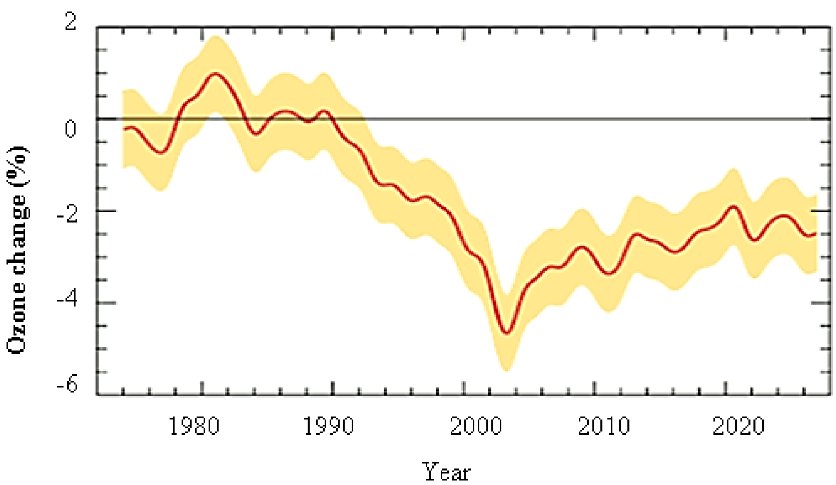


Figure 6. Forecasts of the global depletion level during 1980 and 2020

Fig 7 is the different latitude region depletion fluctuation prediction result of CNN-SVM, Y axis is the year and X axis represents the ozone level in percentage. By naturally latitude impact the ozone concentration around the globe. Compare to the lower latitude, tropics regions ozone level is low. As seen as in the plot the ozone level is low in south latitude and high in north latitude.

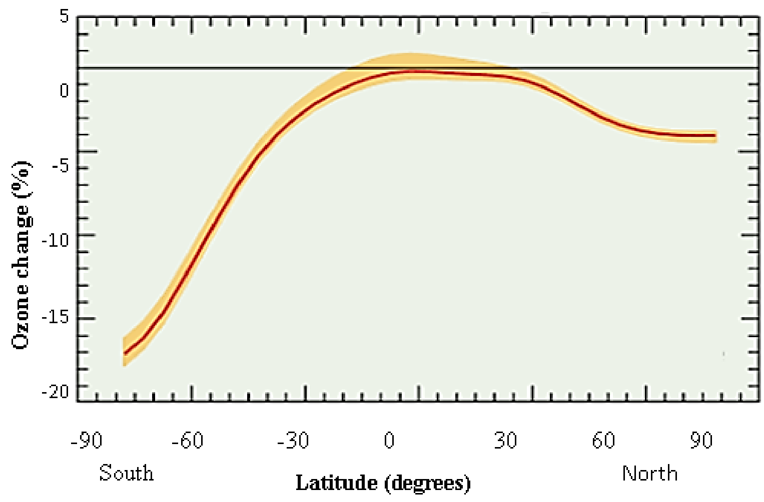


Figure 7. Forecast of depletion levels in various latitudes during 2016 to 2020

Figure 8 depicts the CNN-SVM anticipated depletion in the extremely depleted Antarctica region from 2010 to 2014. Increased stratospheric temperatures can lessen ozone depletion; year-to-year weather fluctuation has a substantial impact on Antarctica ozone. In comparison to the years 1998-2006, the depletion level in 2014 is lower. The level of depletion chemicals in 2014 is lower than it was in 2000.

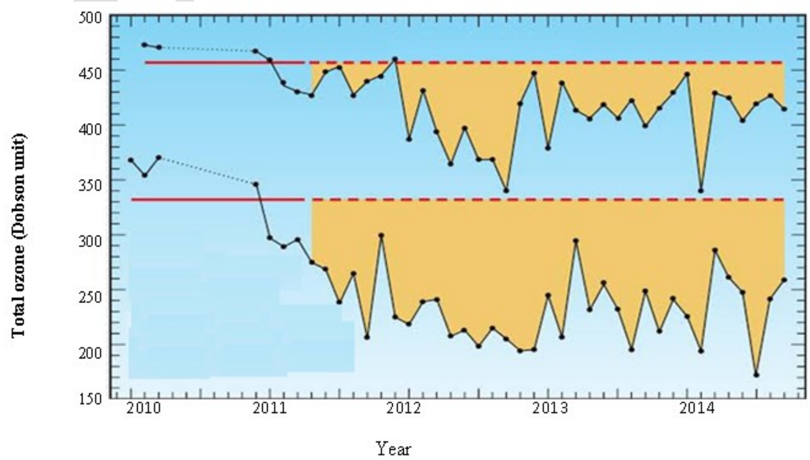


Figure 8. The level of depletion predicted in Antartical region

4.2. Comparative analysis

The findings indicate that a CNN-SVM methodology could significantly assist in the detection of ozone depletion through meteorological image, resulting in a low-cost and low complex forecast of depletion fluctuation. Each neural network's effectiveness was assessed to verify that the proposed CNN-SVM model had higher accuracy. Random Forest, and Decision tree, Google Net, are the neural network classifiers were assessed for performance analysis. The quality was estimated by a number of measures, including accuracy, specificity, and recall, which are superior to those employed by conventional DL networks.

Table 2. Comparison of proposed CNN model with several traditional networks

NETWORKS	Accuracy	Precision	Recall	Specificity	F1 score
Random Forest	97.35	97.17	96.36	95.44	97.07
Decision tree	95.18	94.34	95.53	95.11	95.52
proposed CNN	98.99	98.19	97.21	97.82	98.64

By comparing the maximum capacity for classification over numerous common DL connections, Table.2 highlights the discrepancy. Nevertheless, the proposed CNN-SVM architecture yielded stronger fallouts than the traditional DL networks. The overall f1-Score is increased by 2.59%, 3.52%, and 4.13% with the proposed CNN model respectively.

Table 3. Comparison of proposed SVM model with several traditional networks

NETWORKS	Accuracy	Precision	Recall	Specificity	F1 score
Res Net [28]	97.27	97.17	96.46	95.34	97.17
Alex Net [29]	96.17	95.89	97.33	97.44	96.25
proposed SVM	98.83	98.29	97.23	97.77	98.74

By comparing the maximum capacity for classification over numerous common DL connections, Table.2 highlights the discrepancy. Nevertheless, the proposed CNN-SVM architecture yielded

stronger fallouts than the traditional DL networks. The overall f1-Score is increased by 2.3%, 3.19%, and 0.7% with the proposed SVM model respectively.

Table 4. Performance Analysis of existing model with proposed CNN-SVM model

Authors	Techniques	Performance
Zhu et al	CNN	99.23%
Chauhan and Vamsi	SVM-IF	92.7%
Aslam et al	F_RCNN	95%
Proposed	SW-CNN	99.44%

In [24] SVM-IF model is suggested but its detection performance is affected when handling the complex data. The CNN [17] performance is close to the proposed value, but its generalization capability is low also accuracy is 0.37 less. Faster RCNN [25] is taken more time for training. This comparison proves that proposed model is well suited for depletion level detection compare to other method. Comparing the CNN, SVM-IF, and Faster RCNN, the overall accuracy range is improved by 0.21%, 6.74%, and 4.44%, respectively. The proposed CNN-SVM model obtains high accuracy rate than other existing models.

5. Conclusion

In this paper, an intelligent system is proposed to monitor the depletion level of the stratospheric ozone. Training images are collected through the meteorological satellite and annotated to train the supervised learning model. The hybridization of CNN and SVM is act as an intelligent model. Deeply layered structure CNN extracts the feature and fed to the SVM for classification. SVM convert the nonlinear data into linear and plot into the high dimensional feature space for classification. From the experimental outcomes, the CNN, SVM-IF, and Faster RCNN, the overall accuracy range is improved by 0.21%, 6.74%, and 4.44%, respectively. The overall f1-Score is increased by 2.59%, 3.52%, and 4.13% with the proposed CNN model respectively. The overall f1-Score is increased by 2.3%, 3.19%, and 0.7% with the proposed SVM model respectively. The proposed CNN-SVM model obtains high accuracy rate than other existing models. The experimental findings show that the proposed CNN-SVM framework accomplishes satisfactory prediction accuracy of 99.44%, which is a significant contribution to restricting ozone depletion compounds in high-depletion areas as well as protecting the earth's living organism. In the future, the suggested model will be trained using ozone-depleting compounds (NO x, chlorine) to forecast ozone fluctuation.

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