Rice Diseases Classification by Residual Network 50 (RESNET50) and Support Vector Machine (SVM) Modeling

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Abstract— The rice crop is one of the most important food crops that depend on it globally. Therefore, farmers must preserve the production of this crop from infection with pests and diseases that lead to its destruction through artificial intelligence and deep learning techniques. A hybrid model combining a Residual Network 50 (ResNet50) deep convolutional neural network (CNN) and a support vector machine (SVM) developed diagnoses rice diseases. Farmers or people working in agriculture could use this model to quickly and accurately identify the diseases in their crops and treat them, increasing crop yield and reducing the need for costly and time-consuming manual inspection. ResNet50, a deep learning model effective at image classification tasks, was used to extract features from images of rice plants. SVM was then used to classify the diseases based on these features. The ResNet50 was able to capture complex patterns in the images, while the SVM was able to use these patterns to make accurate classification decisions. This hybrid model allowed for high precision in rice disease diagnosis, achieving an accuracy of approximately 99%.

Keywords—**: **Convolutional Neural Network, Deep Learning, ResNet50, Rice Diseases, Support Vector Machine SVM.

I. Introduction

The world's more than 50% population is dependably fed on rice[1]. According to the FAOSTAT review from the Food and Agriculture Organization of the United Nations, 91.05% of the rice consumed and produced worldwide is in Asia[2]. The remaining rice production is divided among several world regions, comprising 2.95% from Africa, 5.19% from America, 0.67% from Europe, and 0.15% from Oceania[3]. Rice is the most widely grown and valuable crop in the world. Early and precise diagnosis of diseases in rice plants. While farming can aid in minimizing harm and raising productivity, benefiting both the environment and farmers. Various deep convolutional neural networks (CNNs) have opened to diagnose diseases in rice plants with high accuracy. This study combined a multiclass classifier called a support vector machine with ResNet50 to extract features. A deep learning network called ResNet50 has been trained for image classification tasks[4]. It is a convolutional neural network that is composed of 50 layers. It effectively learns complex patterns and features in images[5]. It operates by locating a hyperplane in the training data that most effectively distinguishes between classes. SVMs work best when the data can be divided into distinct classes by a single straight line or when the data is linearly separable[6].

II. RELATED WORK

Several techniques have been used to diagnose and classify rice diseases from images correctly. Most of them use SVM classifiers, deep learning algorithms, and standard image processing techniques[7]. A multi-SVM was employed as the primary classifier, while a CNN model based on AlexNet was used to extract features. Accuracy of 91.37%was achieved with an 80:20 training-to-testing ratio while studying four different diseases, including bacterial, sheath blight, healthy leaves, and rice blast[8]. Additionally, SVM and deep CNN were used to denoise images and classify rice diseases by combining colour and shape data. Two hundred images from seven categories were taken, with an accuracy rate of 87.50%[9].

Furthermore, the researchers present a method for classifying rice pests using an SVM classifier. Images of the five types of rice pests were gathered from Google Images and the Manual for Rice Pest Surveillance. With a 97.5% accuracy rate, the SVM classifier can identify the pest and classify it based on its attributes[10]. The integrated deep CNN and SVM classifier uses a transfer learning technique to enhance the classification model. The model's effectiveness was evaluated using a dataset of 1080 images representing nine different rice illnesses. The model's prediction accuracy throughout the training phase was 97.5% [11].

Additionally, there is a dataset of pests and diseases that affect rice that includes 1426 images and covers eight types of rice diseases. Architectures like VGG16 and InceptionV3 have been used to identify and diagnose rice diseases. Experimental data show that the proposed design can achieve an accuracy of 93.3% [12]. Moreover, the VGG-16-based Framework is trained and evaluated using data from rice fields and the internet. These data are divided into four classes, which together total 1509 images. The predicted model's accuracy is 92.46%[13]. Another study describes various classification schemes for diseases of rice leaves. Using Otsu's approach, images of four different forms of rice plant diseases are segmented. Using the Histogram of Oriented Gradients HOG and Local Binary Patterns LBP, various features are isolated from the segmented area. The properties are then categorized using an SVM, and polynomial Kernel SVM with HOG was used to obtain 94.6% accuracy[14].

III. METHODOLOGY

A hybrid model ResNet50 and a support vector machine (SVM) was developed for rice disease diagnosis; the steps of the suggested model are Data collection, preprocessing stage, feature extraction and flatten stage by ResNet50, and diseases classification stage by SVM. The model's steps are shown in Fig.1.

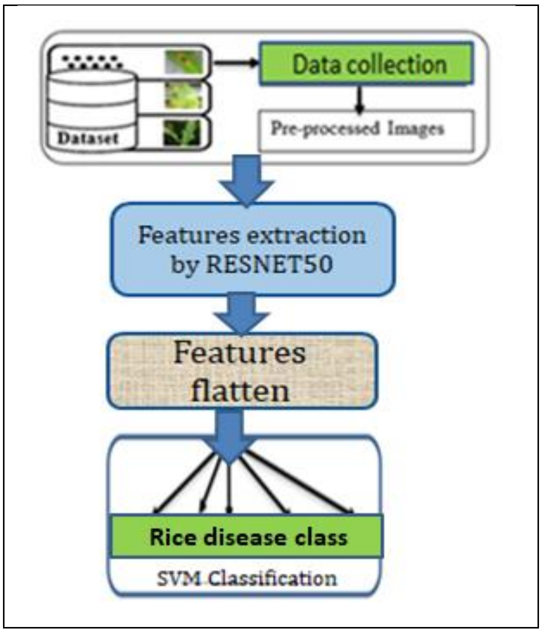

Fig. 1. Model's steps

A. Data Collection

A database available on the Kaggle site was used. The dataset contains normal images and nine different types of rice diseases: Bacterial blight, Brown spot, Bacterial leaf streak, Blast, Dead heart, Downy mildew, Hispa, Sheath blight and Tungro[15].

B. Preprocessing Stage

Many images are needed to train the model for deep learning-based image classification. Therefore, through several data augmentation techniques, such as vertical and horizontal translation up to 3px and random flipping. The type of augmentation process(flop) is shown in Fig.2. All those images were the appropriate 224x224 pixel size for the model. The type

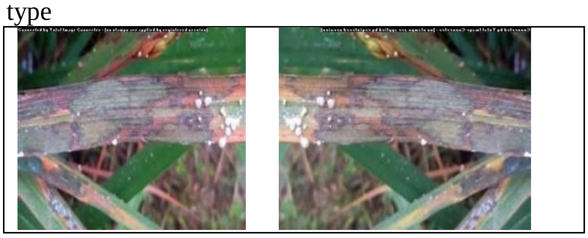

Fig.2. Augmentation images process(flip)

The number and variety of images also expanded to become the total number of 15000 images after the augmentation process, such as(flip, rotation and saturation). The dataset was split into 80% training, 10% validation and 10% testing. The spread of rice diseases after the augmentation process in the dataset is shown in Fig.3.

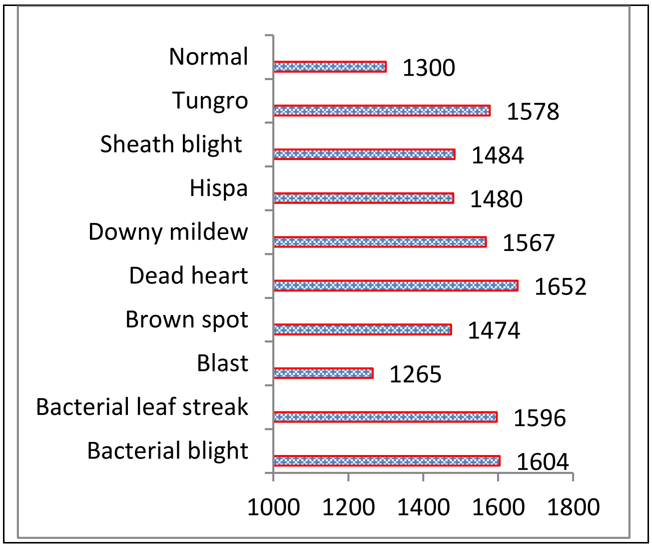

Fig.3. Rice diseases dataset distribution

C. Feature-Extraction and Flatten by (ResNet50)

Visual Recognition. Challenge (ILSVRC), He et al. presented the idea. The Residual Neural Network (ResNet) won the ImageNet Large Scale[16]. Residual Network is abbreviated as ResNet[17]. Instead of aiming to learn all features, a model instead seeks to learn low-level or high-level characteristics for each layer of RESNET50 as it is learned for the current position, using the ImageNet dataset as training material, the deep convolutional neural network ResNet50 was built[18].It is a 50-layer network that contains various layer types, including as fully connected, pooling, and convolutional layers[19]. The primary principle of ResNets50 is to add layer (l) activation to the layer (l+2) output, which is known as the identity shortcut connection[20]. Going deeper has become popular to handle more problems and improve classification accuracy. However, problems like degradation and the vanishing gradient have made it challenging to train deeper networks[21]. Residual learning attempts to address both of these problems. Block residues are seen in Fig.4.

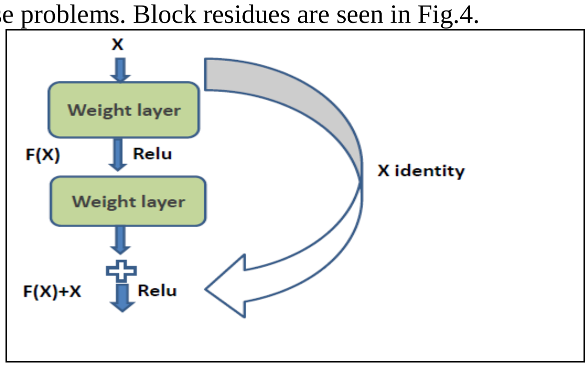

Fig.4. Residual block

The representational strategy of arranged deep neural frameworks reflects a layered, forward-moving process. Image data is transmitted layer by layer. ResNet50 down-samples the input by two, like the pooling layer using 7x7 convolution with stride two at the primary layer; after that, it is down-sampled by two more times before being followed by three characters[22]. A convolution layer, the down-sampling layer, also has a personality association. Similar patterns are repeated a few layers deeper. For each feature map in the final layer, normal pooling produces 1000 element maps (using data from ImageNet), and the result would be a 1000-dimensional vector that was then directly fed into the Softmax layer, making it convolutional[23]. At the conclusion, receive the classification of an image's class. In our suggestion, the classification layer's final layer will be frozen, and an SVM classifier will take its place. Rectified. Linear unit (Relu), a nonlinear activation function utilized in convolutional layers. The 50-layer network architecture of ResNet is utilized for categorization. The multidimensional output of the convolutional and pooling layers is finally flattened into a one-dimensional vector that may be input to the fully connected (dense) layers of the network. The purpose of the flatten operation is to prepare the data for the fully connected layers by unrolling the multidimensional tensors produced by the convolutional layers into a single long vector. This allows the fully connected layers to process the data as a set of features rather than a multidimensional tensor. The flatten operation is typically implemented as a layer in the ResNet50 model and is frequently followed by one or more fully connected layers. ResNet50 Architecture is shown in Fig.5.

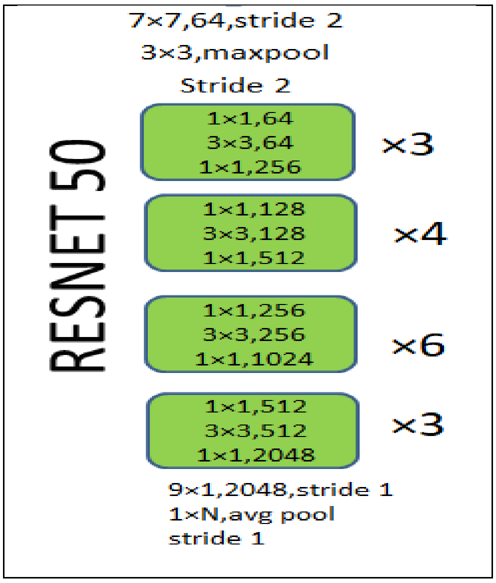

Fig. 5. ResNet50 architecture

The multidimensional output of the convolutional and pooling layers is finally flattened into a one-dimensional vector that may be input to the fully connected (dense) layers of the network. The purpose of the flatten operation is to prepare the data for the fully connected layers by unrolling the multidimensional tensors produced by the convolutional layers into a single long vector. This allows the fully connected layers to process the data as features rather than a multidimensional tensor. The flatten operation is typically implemented as a layer in the ResNet50 model and is frequently followed by one or more fully connected layers.

D. Classification with SVM

Support vector machines (SVMs) are supervised learning models that analyze data for classification or regression[24]. SVMs are particularly well suited for classification tasks where the data is linearly separable. However, they can also be used to categorize data that cannot be separated linearly by transforming it into a higher dimensional space using a kernel method[25]. SVM is widely used for classification by selecting an optimal hyperplane that separates two classes[26]. The margin separates each class's closest data points and the hyperplane[27]. To use an SVM as a classifier with a ResNet50, the output of the ResNet50 can be treated as a set of input features to the SVM. The SVM can then be trained on these features to classify the input data. SVMs can be used as a classifier for multiclass classification problems[28]. Several strategies can be used to extend the basic binary SVM classifier. to handle multiclass classification. One common approach is to use a one-versus-all (OVA) strategy, in which a separate binary SVM classifier is trained for each class to distinguish that class from all of the other classes[29]. At test time, the classifier with the highest confidence score is chosen as the predicted class, and another approach is to use a one-versus-one (OVO) strategy, in which a separate binary SVM classifier is trained for every pair of classes, at test time, the class with the most votes from the individual classifiers is chosen as the predicted classes[30]. Another approach is to use a multiclass SVM algorithm; this approach uses a single SVM classifier that is trained to distinguish between all of the classes at once, rather than training multiple binary classifiers [31].

IV. RESULT AND DISCUSSION

The study's main objective is to combine a feature extraction technique with a classification method on different disease datasets. Based on numerous performance metrics, the effectiveness of the suggested technique is evaluated in this experimental work. The experimental studies were carried out using the Python Colab framework. On a laptop, all programs were executed, i.e. HP Core i5 8th with 128 GB SSD, and Windows 10 Home. Ten of the most common diseases that damage rice plants are included in our dataset of images of rice plant disease. Fifteen thousand images of rice diseases were used. The dataset was split into 80% training, 10% validation and 10% testing. While the ResNet50-SVM model only needed 20ms to make a prediction, it took 28ms for the ResNet50 model using Softmax to complete. The accuracy of ResNet50 with SVM was 99%, and its average testing loss was 0.0348, while ResNet50-Softmax testing accuracy was 98.8%, and its average testing loss was 0.0504. The parameters used in the proposed model is shown in Table 1.

Table 1. The parameters used in the proposed model

Parameters	ResNet5with Softmax	ResNet50 with SVM
Batch-Size	32	32
Optimizer	Adam	Adam
Epoch	80	80
C-SVM	Not available	0.0001

C: classification SVM parameter.

When noted training and validation accuracy of an SVM with Softmax, the classifier SVM performs very well than Softmax, as shown in Fig.6 and Fig.7.

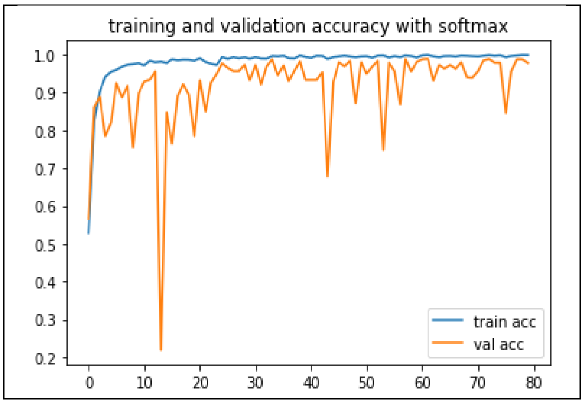

Fig. 6. Training and validation accuracy with softmax

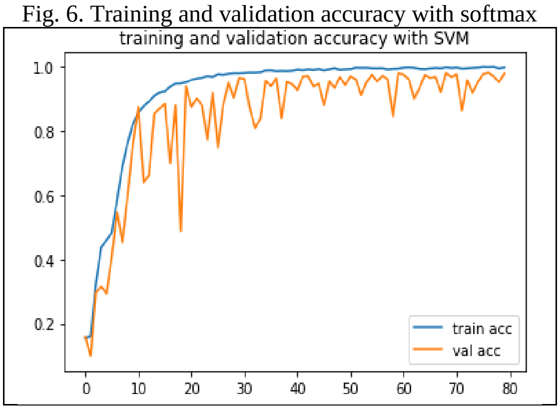

Fig. 7. Training and validation accuracy with SVM

Finally, the model may be used to analyze new images with high prediction accuracy during the model evaluation stage. The final output would be like as in Fig.8.

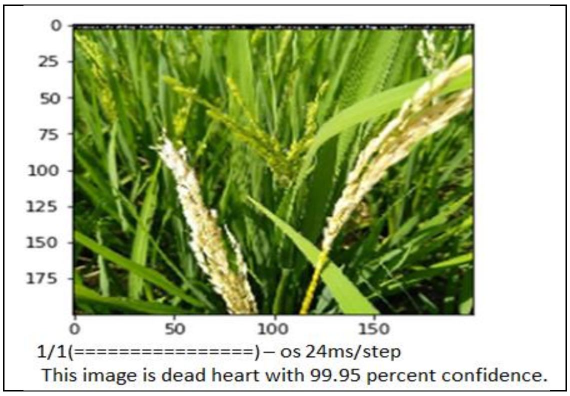

Fig. 8. Samples of a prediction image

When comparing the accuracy and number of parameters of different deep learning models such as AlexNet, Vgg19, Inception v3, Inception ResNet v2, Xception, and Vgg16, we find that RESNET50 is higher accuracy than the others, as shown in Table 2.

Table 2. The accuracy of ResNet50 and SVM vs some other CNN techniques.

Model	Accuracy	Parameters
AlexNet	94.4%	46.7 m
Vgg19	73.3%	20.5 m
Inception v3	68%	23.9 m
Inception ResNet v2	87.4%	55.9 m
Proposed Resnet50+SVM	99%	23 M

A model's performance may also be impacted by the number of its parameters, with models with a higher number of parameters requiring more computational resources and time to train. The ResNet50+SVM model, a hybrid model combining a CNN (**ResNet50**) with an SVM, has the highest accuracy at 99%. It also has the lowest number of parameters at 20 million. The ResNet50 model with Softmax has an accuracy of 98.8% and also has 20 million parameters. The models with the lowest accuracies are the Vgg19 and Inception v3, both CNN-only models.

V. CONCLUSION

A hybrid model combining a ResNet50 and a support vector machine (SVM) demonstrated high accuracy for rice disease diagnosis using a dataset from Kaggle. The ResNet50 extracted features from rice plants' images, while the SVM used these features to make accurate classification decisions. Combining these two models resulted in an accuracy of approximately 99% for classifying normal leaves and nine types of rice diseases. This model can be used to develop an automated system for identifying and diagnosing rice diseases, which could significantly benefit farmers and agricultural professionals by improving crop yield and reducing the need for costly and time-consuming manual inspection.

REFERENCES

[1] C. Calpe, Rice in world trade, Part II. Status of the world rice market, Proc. 20 Th Sess. Int. Rice Comm. (2002).

[2] P. Varma, P. Varma, Ghosh, Rice productivity and food security in India, Springer, 2017.

[3] M.K. Papademetriou, Rice production in the Asia-Pacific Region: Issues and perspectives. In'Bridging the Rice Yield Gap in the Asia-Pacific Region'. FAO, UN, Bangkok, Thailand, RAP Publ. 16 (2000) 2000.

[4] Y. Tang, Deep learning using linear support vector machines, ArXiv Prepr. ArXiv1306.0239. (2013).

[5] A.S.B. Reddy, D.S. Juliet, Transfer learning with ResNet-50 for malaria cell-image classification, in: 2019 Int. Conf. Commun. Signal Process., IEEE, 2019:pp.945–949.http://doi.org/10.1109/ICCSP.2019.8697909.

[6] S. Almabdy, L. Elrefaei, Deep convolutional neural network-based approaches for face recognition, Appl. Sci. 9(2019)4397. https://doi.org/10.3390/app9204397

[7] F. Jiang, Y. Lu, Y. Chen, D. Cai, G. Li, Image recognition of four rice leaf diseases based on deep learning and support vector machine, Comput. Electron. Agric. 179 (2020) 105824. https://doi.org/10.1016/j.compag.2020.105824

[8] V.K. Shrivastava, M.K. Pradhan, S. Minz, M.P. Thakur, Rice plant disease classification using transfer learning of deep convolution neural network, Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. 3 (2019)631–635.https://doi.org/10.5194/isprs-archives-XLII-3-W6-631-2019

[9] R. Rajmohan, M. Pajany, R. Rajesh, D.R. Raman, U. Prabu, Smart paddy crop disease identification and management using deep convolution neural network and SVM classifier, Int. J. Pure Appl. Math. 118 (2018) 255–264.

[10] P.K. Sethy, C. Bhoi, N.K. Barpanda, S. Panda, S.K. Behera, A.K. Rath, Pest Detection and Recognition in Rice Crop Using SVM in Approach of Bag-Of-Words, in: Int. Conf. Softw. Syst. Process., 2017.

[11] M.J. Hasan, S. Mahbub, M.S. Alom, M.A. Nasim, Rice disease identification and classification by integrating support vector machine with deep convolutional neural network, in: 2019 1st Int. Conf. Adv. Sci. Eng. Robot. Technol., IEEE, 2019: pp. 1–6. https://doi.org 10.1109/ICASERT.2019.8934568

[12] C.R. Rahman, P.S. Arko, M.E. Ali, M.A.I. Khan, S.H. Apon, F. Nowrin, A. Wasif, Identification and recognition of rice diseases and pests using convolutional neural networks, Biosyst. Eng. 194 (2020)112–

120.https://doi.org/10.1016/j.biosystemseng.2020.03.020

[13] S. Ghosal, K. Sarkar, Rice leaf diseases classification using CNN with transfer learning, in: 2020 IEEE Calcutta Conf., IEEE, 2020: pp. 230–236. https://doi.org/10.1109/CALCON49167.2020.9106423.

[14] M.E. Pothen, M.L. Pai, Detection of rice leaf diseases using image processing, in: 2020 Fourth Int. Conf. Comput. Methodol. Commun., IEEE, 2020: pp. 424–430.https://doi.org/10.1109/ICCMC48092.2020.ICCMC-00080.

[15] Paddy Doctor: Paddy Disease Classification | Kaggle, (n.d.).https://www.kaggle.com/competitions/paddy-disease-classification/data (accessed February 13, 2023). https://doi.org/10.17632/fwcj7stb8r.1.

[16] "ImageNet Object Localization Challenge | Kaggle." https://www.kaggle.com/competitions/imagenet-object-localization-challenge/data (accessed Mar. 24, 2023).

[17] N. Sharma, V. Jain, A. Mishra, An analysis of convolutional neural networks for image classification, Procedia Comput. Sci. 132 (2018) 377–384.https://doi.org/10.1016/j.procs.2018.05.198.

[18] H. Yu, S. Kim, SVM Tutorial-Classification, Regression and Ranking., Handb. Nat. Comput. 1 (2012) 479–506.

[19] J. Sharma, O.-C. Granmo, M. Goodwin, J.T. Fidje, Deep convolutional neural networks for fire detection in images, in: Int. Conf. Eng. Appl. Neural Networks, Spriner,2017:pp.183–193.https://doi.org/10.1007/978-3-319-65172-9_16.

[20] B. Leibe, J. Matas, N. Sebe, M. Welling, Springer International Publishing: Cham, (2016).

[21] L. Metz, N. Maheswaranathan, R. Sun, C.D. Freeman, B. Poole, J. Sohl-Dickstein, Using a thousand optimization tasks to learn hyperparameter search strategies, ArXiv Prepr. ArXiv2002.11887. (2020). https://doi.org/10.48550/arXiv.2002.11887.

[22] M. Chiaberge, A. Tartaglia, Machine Learning Algorithms for Service Robotics Applications in Precision Agriculture, (2018).

[23] L. Baecker, R. Garcia-Dias, S. Vieira, C. Scarpazza, A. Mechelli, Machine learning for brain age prediction: Introduction to methods and clinical applications, EBioMedicine. 72 (2021) 103600.https://doi.org/10.1016/j.ebiom.2021.103600.

[24] S. Ghosh, A. Dasgupta, A. Swetapadma, A study on support vector machine based linear and non-linear pattern classification, in: 2019 Int. Conf. Intell. Sustain. Syst., IEEE, 2019: pp. 24–28. https://doi.org/10.1109/ISS1.2019.8908018

[25] M.A. Khan, K. Abbas, M.M. Su'ud, A.A. Salameh, M.M. Alam, N. Aman, M. Mehreen, A. Jan, N.A.A.B.N. Hashim, R.C. Aziz, Application of Machine Learning Algorithms for Sustainable Business Management Based on Macro-Economic Data: Supervised Learning Techniques Approach, Sustbiity.14(2022)9964.https://doi.org/10.3390/su14169964.

[26] A. Rana, P. Vaidya, G. Gupta, A comparative study of quantum support vector machine algorithm for handwritten recognition with support vector machine algorithm, Mater. Today Proc. 56 (2022) 2025–2030. https://doi.org/10.1016/j.matpr.2021.11.350.

[27] Z. Mehmood, S. Asghar, Customizing SVM as a base learner with AdaBoost ensemble to learn from multiclass problems: A hybrid approach AdaBoost-MSVM, Knowledge-Based Syst. 217 (2021) 106845. https://doi.org/10.1016/j.knosys.2021.106845

[28] J. Park, Y. Choi, J. Byun, J. Lee, S. Park, Efficient differentially private kernel support vector classifier for multiclass classification, Inf. Sci. (Ny). 619 (2023) 889–907. https://doi.org/10.1016/j.ins.2022.10.075.

[29] K.-B. Duan, S.S. Keerthi, Which is the best multiclass SVM method? An empirical study, in: Mult. Classif. Syst. 6th Int. Work. MCS 2005, Seaside, CA, USA, June 13-15, 2005. Proc. 6, Springer, 2005: pp. 278–285. https://doi.org/10.1007/11494683_28

[30] Z.-L. Zhang, C.-Y. Zhang, X.-G. Luo, Q. Zhou, A multiple classifiers system with roulette-based feature subspace selection for one-vs-one scheme, Pattern Anal. Appl. (2022) 1–18.

[31] S. Kang, Using binary classifiers for one-class classification, Expert Syst. Appl. 187 (2022) 115920.https://doi.org/10.1016/j.eswa.2021.115920.