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A comparative study of pre-trained models for image feature extraction in weather image classification using orange data mining

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ABSTRACT

This paper presents a detailed comparative analysis of pre-trained models for feature extraction in the domain of weather image classification. Utilizing the orange data mining toolkit, we investigated the effectiveness of six prominent pre-trained models-InceptionV3, SqueezeNet, VGG-16, VGG-19, painter, and DeepLoc-in accurately classifying weather phenomena images. Among these models, InceptionV3, in conjunction with neural networks, emerged as the most effective, achieving a classification accuracy (CA) of 96.1%. Painter and SqueezeNet also showed strong performance, with accuracies of 95.1% and 86.7%, respectively, although they were surpassed by InceptionV3. VGG-16 and VGG-19 provided moderate accuracy, while DeepLoc underperformed significantly with a maximum accuracy of 56%. Neural networks consistently outperformed other classifiers across all models. This study highlights the critical importance of selecting appropriate pre-trained models to enhance the accuracy and reliability of weather image classification systems.

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1. INTRODUCTION

Weather image classification involves automatically categorizing images based on depicted weather conditions, such as sunny, cloudy, rainy, snowy, foggy, and stormy [1]. This task necessitates the development of sophisticated machine learning models, particularly convolutional neural networks (CNNs), that can accurately recognize and classify diverse weather patterns. The challenge lies in designing algorithms that reliably analyze weather-related imagery, providing precise labels essential for improving weather forecasting accuracy, which is crucial for disaster preparedness and response [2]-[4].

Accurate weather image classification is vital across various sectors. In transportation, it enhances road safety by enabling vehicles to detect and adapt to changing weather conditions [5], [6]. In agriculture, it improves crop management and irrigation through effective monitoring of weather conditions [7], [8]. Environmental monitoring agencies rely on weather classification for tracking air quality and other ecological factors, contributing to environmental protection [9], [10]. Additionally, it is crucial for assessing the impact of weather on critical infrastructure, ensuring safety and durability [11], [12].

Advanced techniques are employed to address the challenges of weather image classification. CNNs are widely adopted due to their proficiency in learning hierarchical features from images [2], [3]. Transfer learning, where pre-trained CNN models are fine-tuned [3], [4], and ensemble learning methods, which combine multiple models, further enhance classification performance [5], [6]. Recurrent neural networks (RNNs) are pivotal in capturing temporal dependencies in sequences of weather images [13], [14]. Data augmentation techniques, such as rotations and translations, help address limited training data by generating additional samples [7], [8]. Spatial-temporal models, attention mechanisms, and the fusion of data from diverse sources, including satellite imagery and radar data, contribute to more accurate predictions [15]-[19]. Semi-supervised and weakly supervised learning approaches leverage both labeled and unlabeled data, especially in scenarios with limited labeled data [20]-[22]. The selection of suitable techniques depends on specific problem requirements, dataset characteristics, computational resources, and desired accuracy. Continuous exploration of novel methodologies and engagement with the latest research developments are essential for enhancing the efficacy of weather image classification systems, driving innovation, and advancing the field.

2. RELATED WORK

The classification and prediction of weather conditions based on image data has become an increasingly important field of research, driven by advancements in deep learning and computer vision. Accurate weather classification not only improves forecasting accuracy but also enhances various applications, such as autonomous driving, environmental monitoring, and disaster management. Traditional methods of weather prediction rely on complex meteorological models, satellite data, and human expertise, which are often resource-intensive and not always practical for real-time applications [23]. In contrast, recent developments in machine learning, particularly CNNs, have demonstrated significant potential for automating and improving weather classification tasks [23], [24].

Deep learning techniques, especially CNNs, have been widely used in image classification tasks, and their application in weather image classification has gained substantial attention. For instance, Cao and Yang [23] developed a CNN-based model for weather classification that outperformed several state-of-the-art methods, achieving a remarkable 98% accuracy. Their approach utilized data augmentation techniques to overcome the challenges posed by imbalanced datasets and varying weather conditions. Similarly, Li *et al.* [24] introduced a vision transformer (ViT)-based model for multi-class weather image classification, demonstrating the advantages of using transformer architectures over traditional CNNs. Their model achieved an impressive accuracy of 92.83% across 14 different weather classes [25].

Moreover, hybrid models that combine CNNs with other machine learning techniques, such as support vector machines (SVMs), have been explored to enhance classification performance. For example, a study by Triva *et al.* [26] developed a CNN-SVM hybrid model that improved classification accuracy (CA) for various weather conditions, particularly in adverse environments like fog and rain. This hybrid approach proved effective in applications such as autonomous driving, where precise weather condition recognition is critical for safety [26].

Beyond CNNs, the use of cloud image classification for weather prediction has also emerged as a promising approach. Cao and Yang [23] developed a mobile application that utilizes CNNs to classify cloud images into four categories: rain clouds, fair-weather clouds, tornado clouds, and fog. Their system demonstrated high accuracy in identifying rain and fog, though further improvements were needed for tornado prediction [23]. This development reflects the growing interest in portable, real-time weather prediction tools that leverage modern smartphone capabilities.

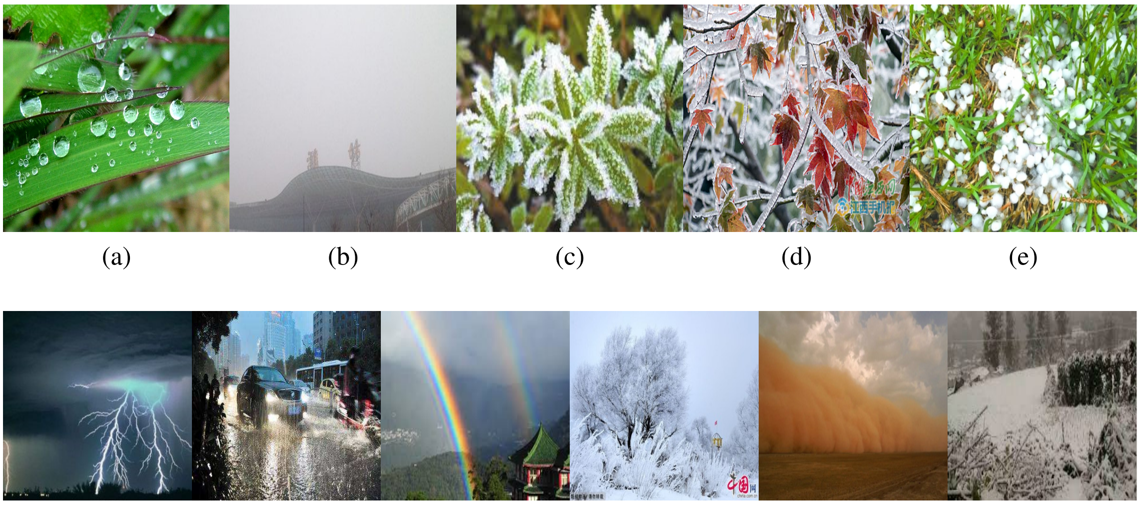
Other researchers have also focused on the challenges of weather classification in specific domains, such as vehicle environments. In one such study, a CNN model was designed to classify weather conditions from front-view camera images in autonomous vehicles. The model achieved high performance, with an F1 measure of 98.3%, demonstrating its potential for real-world applications in autonomous driving [26]. Overall, the integration of deep learning techniques, particularly CNNs, with weather image data has revolutionized the field of weather classification.

This study focuses on evaluating pre-trained models for feature extraction in weather image classification using orange data mining. Models such as InceptionV3, VGG16, VGG19, SqueezeNet, painter, and DeepLoc were assessed, with InceptionV3 consistently outperforming others across various classifiers, underscoring its effectiveness for this task.

3. MATERIAL AND METHODS

This study uses the weather phenomenon image database (WEAPD), developed by Xiao *et al.* [27], as the main dataset. WEAPD consists of 6,877 images, which are organized into 11 different categories as shown in Figure 1, including (a) dew, (b) fog/smoke, (c) frost, (d) glaze, (e) hail, (f) lightning, (g) rain, (h) rainbow, (i) frost, (j) sandstorm, and (k) snow, which are classified based on their visual shapes and color attributes. All example images are presented in Figure 1. To facilitate comprehensive model evaluation, K-fold cross validation is applied, which divides the dataset into several subsets for training and validation.

Weather image classification was performed using the orange data mining toolkit, an open-source platform developed in Python at the University of Ljubljana, Slovenia [28]. Orange supports various machine learning tasks, including regression, classification, and clustering, making it ideal for educational use and prototyping.



(a) (b) (c) (d) (e)

(f) (g) (h) (i) (j) (k)

Figure 1. The representative examples of 11 WEAPD; (a) dew, (b) fog/smog, (c) frost, (d) glaze, (e) hail, (f) lightning, (g) rain, (h) rainbow, (i) rime, (j) sandstorm, and (k) snow

In this study, pre-trained models such as InceptionV3, VGG16, VGG19, SqueezeNet, painter, and DeepLoc were employed for image embedding to generate vector representations of each image. These embeddings were then used to train classifiers including neural networks, K-nearest neighbors (KNN), and SVM. Transfer learning techniques were applied, leveraging limited data from fruits and vegetables to enhance model accuracy and reduce data requirements [29]-[34]. Model performance was assessed using orange's test and score widget, which calculated metrics like accuracy, precision, recall, and F1-score. The use of K-fold cross validation enhanced the robustness of model evaluation by providing comprehensive metrics such as CA, AUC, and F1-score across different test folds. Detailed experiment parameters are presented in Table 1.

Table 1. Evaluating the classification of weather phenomenon image using InceptionV3 as a feature

Model	Algorithm parameter
Neural network	Neural in hidden layer = 100
	Activation = ReLu
	Solver = Adam
	Regularization, α = 0.0001
	Maximal number of iterations = 200
KNN	Euclidean distance, Manhattan distance, Chebyshev distance
	Number of neighbors = 5
SVM (Linear)	Kernel = Linear, Polynomial, RBF, Sigmoid
	Optimization parameters (Numerical tolerance = 0.0010)
	Optimization parameters (Iteration limit = 100)

4. RESULTS AND DISCUSSION

A systematic empirical evaluation of multiple classification approaches was conducted for weather image categorization using the WEAPD [27]. The pre-trained InceptionV3 model played a pivotal role in our approach, serving as a feature extractor within the Orange toolkit, generating vector representations for each image, and enhancing the feature space for classification. Among the various machine learning classifiers applied, neural networks demonstrated superior performance in weather image classification. The integration of InceptionV3 embeddings with neural networks resulted in high accuracy and precision, with the neural network model excelling in capturing complex patterns within the dataset.

The experimental results, summarized in Table 2, indicate that the combination of InceptionV3 for feature extraction and classifiers such as neural networks provides a successful strategy for high-performance weather image classification. This approach enabled efficient feature extraction and demonstrated the potential of advanced classifiers to achieve accurate categorization of weather phenomena with a high level of precision. Specifically, the neural network model with InceptionV3 embeddings achieved an AUC of 0.971, a CA of 96.1%, an F1-score of 0.778, and a matthews correlation coefficient (MCC) of 0.757, indicating a strong and balanced classification performance.

Other classifiers, such as KNN with various distance metrics, and SVM with different kernels, showed varying levels of performance. KNN models, while achieving respectable results, exhibited lower precision and recall balance compared to neural networks. The SVM models, particularly with Polynomial and RBF kernels, performed well, but still fell short of the neural network model in terms of overall accuracy and precision.

Overall, the neural network model with InceptionV3 embeddings proved to be the most effective approach for weather image classification, surpassing other classifiers in terms of both accuracy and precision. This study emphasizes the effectiveness of combining pre-trained models for feature extraction with advanced classifiers, highlighting the critical importance of selecting appropriate models and metrics for achieving high-performance image classification

Table 2. Performance metrics for weather classification using InceptionV3 embeddings as a feature

Model	Area under an ROC curve	Classification accuracy	F1-score	Precision	Recall	MCC
Neural network	0.971	0.961	0.778	0.792	0.765	0.757
KNN (Euclidean distance)	0.889	0.940	0.603	0.757	0.501	0.586
KNN (Manhattan distance)	0.886	0.941	0.603	0.773	0.494	0.590
KNN (Chebyshev distance)	0.841	0.930	0.503	0.702	0.391	0.491
SVM (Linear)	0.962	0.952	0.723	0.762	0.688	0.698
SVM (Polynomial)	0.966	0.958	0.769	0.761	0.778	0.746
SVM (RBF)	0.968	0.959	0.773	0.773	0.773	0.750
SVM (Sigmoid)	0.949	0.934	0.685	0.600	0.797	0.657

4.1. Comparison with other image embeddings

In our experiments, InceptionV3 was used for image embedding feature extraction. We performed a detailed comparative analysis with other methods, including SqueezeNet, VGG-16, VGG-19, painters, and DeepLoc, to evaluate the effectiveness of InceptionV3 relative to these alternative techniques. This comparison aimed to assess the reliability and robustness of InceptionV3 in the context of image feature extraction. By examining these different methods, we aimed to better understand the performance and advantages of InceptionV3 compared to other feature extraction methodologies. The architecture is illustrated in Figure 2.

4.1.1. Experimental results using SqueezeNet embeddings

The experimental results, as presented in Table 3, provide a thorough evaluation of various classifiers utilizing SqueezeNet embeddings for weather classification. Among the tested models, the neural network classifier emerged as the optimal choice, achieving the highest accuracy of 86.7% across key evaluation metrics, including AUC, F1-score, precision, recall, and MCC. This highlights the strong synergy between the neural network architecture and the features extracted by SqueezeNet.

KNN classifiers, despite using different distance metrics, achieved similar performance, with accuracies around 77-78%. However, these models were outperformed by the neural network classifier, indicating that while KNNs performed reasonably well, they were less effective in leveraging SqueezeNet embeddings.

SVM classifiers demonstrated varied performance depending on the kernel used. Polynomial and RBF kernels were the most competitive, achieving an accuracy of 78%, comparable to the best KNN models.

In contrast, the linear kernel lagged behind with an accuracy of 71.4%, and the Sigmoid kernel performed poorly, with a significantly lower accuracy of 37.4%. This suggests that the Sigmoid kernel is not well-suited for SqueezeNet features in the context of weather classification.

Overall, the neural network classifier was the most effective model when paired with SqueezeNet embeddings, with SVM classifiers using polynomial or RBF kernels being the closest competitors. KNN models, while performing adequately, did not match the accuracy of neural networks or the top-performing SVM kernels. The Sigmoid SVM kernel notably underperformed, reinforcing the importance of selecting appropriate kernels for optimal classification results.

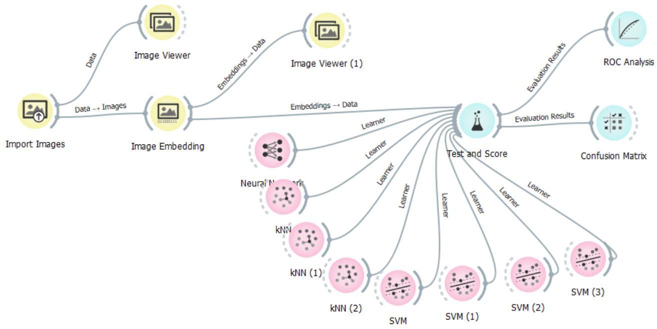


Figure 2. Structure for utilizing orange data mining in image classification

Table 3. Evaluating the classification of weather phenomenon image using SqueezeNet embeddings as features

Model	Area under an ROC curve	Classification accuracy	F1-score	Precision	Recall	MCC
Neural network	0.983	0.847	0.846	0.846	0.847	0.829
KNN (Euclidean distance)	0.947	0.777	0.771	0.776	0.777	0.752
KNN (Manhattan distance)	0.946	0.778	0.772	0.777	0.778	0.752
KNN (Chebyshev distance)	0.938	0.752	0.743	0.751	0.752	0.724
SVM (Linear)	0.967	0.714	0.714	0.719	0.714	0.683
SVM (Polynomial)	0.977	0.783	0.780	0.781	0.783	0.759
SVM (RBF)	0.977	0.785	0.782	0.786	0.785	0.761
SVM (Sigmoid)	0.870	0.374	0.397	0.500	0.374	0.319

4.1.2. Experimental results using VGG-16 embeddings

The experimental results in Table 4 present a comprehensive analysis of classifier performance when paired with VGG-16 embeddings for weather classification. Among the models tested, the neural network classifier emerged as the top performer, achieving the highest accuracy of 84% across key metrics, including AUC, F1-score, precision, recall, and MCC. This indicates a strong synergy between the neural network architecture and VGG-16 features, demonstrating the effectiveness of this combination for accurate weather classification.

KNN classifiers, while performing reasonably well with accuracies in the range of 74-75%, were outperformed by the neural network model. The variations in distance metrics had a marginal impact on KNN performance, but these models did not match the accuracy levels of neural networks when utilizing VGG-16 embeddings.

SVM classifiers exhibited varied performance based on the kernel used. Polynomial and RBF kernels were the most competitive among SVMs, achieving an accuracy of around 76%, comparable to the best KNN models. However, the linear kernel showed lower accuracy at 71.2%, and the Sigmoid kernel significantly underperformed, with an accuracy of 57.8%, indicating its unsuitability for VGG-16 features in this task.

Overall, the neural network classifier proved to be the most effective model when paired with VGG-16 embeddings, with SVMs using polynomial or RBF kernels as the closest competitors. KNN classifiers, although performing adequately, did not achieve the same level of accuracy as neural networks or top-performing SVM kernels. The Sigmoid SVM kernel once again demonstrated significant weaknesses in this context.

Table 4. Evaluating the classification of weather phenomenon image using VGG-16 embeddings as features

Model	Area under an ROC curve	Classification accuracy	F1-score	Precision	Recall	MCC
Neural network	0.982	0.840	0.840	0.841	0.840	0.822
KNN (Euclidean distance)	0.942	0.754	0.749	0.763	0.754	0.727
KNN (Manhattan distance)	0.941	0.747	0.741	0.756	0.747	0.719
KNN (Chebyshev distance)	0.939	0.734	0.728	0.745	0.734	0.705
SVM (Linear)	0.969	0.712	0.712	0.718	0.712	0.680
SVM (Polynomial)	0.975	0.764	0.763	0.776	0.764	0.739
SVM (RBF)	0.974	0.760	0.761	0.771	0.760	0.734
SVM (Sigmoid)	0.939	0.578	0.573	0.649	0.578	0.545

4.1.3. Experimental results using VGG-19 embeddings

The experimental results in Table 5 show that the neural network classifier performed best with VGG-19 embeddings, making it the most effective choice for weather classification. The neural network achieved an accuracy of 82% and excelled across all evaluation metrics, including AUC, F1-score, precision, recall, and MCC.

KNN classifiers, regardless of the distance metric used, showed moderate performance with accuracies ranging from 71% to 74%. The choice of distance metric had little impact on the KNN results. SVM classifiers with polynomial, RBF, and linear kernels achieved similar accuracies around 71%, close to those of the KNN classifiers. However, the Sigmoid kernel underperformed significantly, with an accuracy of 55%, indicating it was not well-suited for use with VGG-19 features.

In summary, the neural network was the top-performing model with VGG-19 embeddings, achieving an accuracy of 82%. SVM and KNN classifiers had lower performance, with accuracies in the low 70% range, while the Sigmoid kernel was notably less effective in this context.

Table 5. Evaluating the classification of weather phenomenon image using VGG-19 embeddings as features

Model	Area under an ROC curve	Classification accuracy	F1-score	Precision	Recall	MCC
Neural network	0.978	0.820	0.820	0.822	0.820	0.799
KNN Euclidean	0.939	0.744	0.738	0.750	0.744	0.715
KNN Manhattan	0.928	0.788	0.732	0.746	0.738	0.708
KNN Chebyshev	0.929	0.714	0.708	0.722	0.714	0.682
SVM linear	0.967	0.714	0.712	0.717	0.714	0.682
SVM Polynomial	0.968	0.711	0.703	0.750	0.711	0.686
SVM RBF	0.968	0.712	0.705	0.743	0.712	0.686
SVM Sigmoid	0.924	0.550	0.547	0.635	0.550	0.514

4.1.4. Experimental results using painter embeddings

The experimental results in Table 6 demonstrate that the neural network classifier achieved the best performance with painter embeddings for weather classification, with an accuracy of 95.1% and high scores across all evaluation metrics, including AUC, F1-score, precision, recall, and MCC. This suggests a strong compatibility between the neural network and painter embeddings for accurate weather classification.

KNN classifiers also performed well, with the Manhattan distance metric achieving an accuracy of 93.8%, slightly higher than the Euclidean metric at 93.6%. The Chebyshev metric was less effective, resulting in an accuracy of 92.4. SVM classifiers performed competitively with painter embeddings, with polynomial, RBF, and linear kernels achieving accuracies between 94% and 95%. The polynomial kernel achieved the highest accuracy among the SVM classifiers at 94.6%, while the Sigmoid kernel had a lower accuracy of 90%, indicating it was less suitable for this task.

In summary, neural networks, SVM kernels, and KNN classifiers all achieved strong performance above 90% accuracy with painter embeddings. The neural network classifier was the top performer with an accuracy of 95.1%, highlighting the importance of selecting suitable classifiers and distance metrics based on the data's characteristics.

4.1.5. Experimental results using DeepLoc embeddings

The experimental results in Table 7 show that DeepLoc embeddings were less effective for weather classification compared to other embedding methods. The neural network classifier performed the best with

Table 6. Evaluating the classification of weather phenomenon image using painter embeddings as features

Model	Area under an ROC curve	Classification accuracy	F1-score	Precision	Recall	MCC
Neural network	0.961	0.951	0.724	0.744	0.704	0.697
KNN Euclidean	0.887	0.936	0.579	0.720	0.485	0.559
KNN Manhattan	0.886	0.938	0.590	0.741	0.494	0.570
KNN Chebyshev	0.829	0.924	0.450	0.647	0.345	0.436
SVM linear	0.949	0.943	0.675	0.690	0.660	0.644
SVM Polynomial	0.951	0.946	0.694	0.715	0.675	0.665
SVM RBF	0.953	0.944	0.692	0.687	0.697	0.661
SVM Sigmoid	0.930	0.900	0.585	0.468	0.781	0.555

DeepLoc embeddings, achieving an accuracy of 56%, but this was still significantly lower than accuracies obtained with other embeddings, which ranged from 86% to 95%. KNN classifiers showed even lower accuracy, around 47%, regardless of the distance metric used. SVM classifiers performed poorly as well, with accuracies ranging from 22.8% to 47.4%, depending on the kernel. These results suggest that DeepLoc embeddings are not well-suited for weather classification tasks.

Table 7. Evaluating the classification of weather phenomenon image using DeepLoc embeddings as features

Model	Area under an ROC curve	Classification accuracy	F1-score	Precision	Recall	MCC
Neural network	0.886	0.560	0.559	0.559	0.560	0.508
KNN Euclidean	0.816	0.474	0.468	0.473	0.474	0.413
KNN Manhattan	0.817	0.477	0.470	0.477	0.477	0.417
KNN Chebyshev	0.800	0.439	0.432	0.437	0.439	0.374
SVM Linear	0.816	0.474	0.468	0.473	0.474	0.413
SVM Polynomial	0.789	0.272	0.231	0.360	0.272	0.222
SVM RBF	0.843	0.379	0.367	0.413	0.379	0.319
SVM Sigmoid	0.746	0.228	0.183	0.262	0.228	0.154

4.2. Comparative analysis of experimental findings across various image embeddings

The experimental outcomes, as detailed in Tables 2-7, indicate that the neural network classifier consistently surpassed other classifiers across all tested image embeddings, establishing it as the most effective approach for weather image classification. The highest accuracy was observed with the InceptionV3 embedding, achieving 96.1%, closely followed by the painter embedding at 95.1%. The SqueezeNet, VGG-16, and VGG-19 models yielded accuracies of 86.7%, 84%, and 82%, respectively. SVM with polynomial or RBF kernels emerged as the most competitive alternatives to neural networks, outperforming the KNN classifiers. Although KNN achieved reasonably good accuracy, its performance was inferior to that of SVM and neural networks. Notably, the DeepLoc embedding was an outlier, with the neural network classifier attaining only 56% accuracy, signifying that this embedding was less suitable for weather classification across all classifiers.

Within the KNN variants, the choice of distance metric generally did not exert a significant influence on performance, although in certain instances, the Manhattan distance provided a marginal improvement over Euclidean distance. The Sigmoid kernel for SVM consistently underperformed across all embeddings, with accuracy dropping as low as 22.8%. In summary, neural networks emerged as the most effective classifier across all image embeddings, with InceptionV3 achieving the highest accuracy at 96.1%. While SVM and KNN classifiers produced competitive results, they were generally outperformed by neural networks. The DeepLoc embedding was found to be unsuitable for this classification task across all evaluated classifiers.

5. CONCLUSION

In this study, we compared several pre-trained models for feature extraction in weather image classification using the orange data mining toolkit. The models evaluated were InceptionV3, SqueezeNet, VGG-16, VGG-19, painter, and DeepLoc, which were tested with neural networks, KNN, and SVM using different kernels. Our findings show that InceptionV3 was the most effective model, achieving the highest CA of 96.1% when paired with neural networks. It also excelled in other evaluation metrics such as AUC, F1-score, precision, recall, and MCC. Painter and SqueezeNet also performed well, with accuracies of 95.1% and 86.7%

respectively, while VGG-16 and VGG-19 were less effective with accuracies of 84% and 82%. DeepLoc significantly lagged behind, with only a 56% accuracy.

Additionally, neural networks were consistently superior to KNN and SVM classifiers across all models. Among SVM kernels, Polynomial and RBF kernels were competitive, but still not as effective as neural networks. The Sigmoid kernel underperformed, emphasizing its unsuitability for this task. This analysis highlights the importance of choosing the right pre-trained model for enhancing CA in weather image classification tasks. The optimal performance achieved by InceptionV3 and neural networks suggests this combination as the best approach for similar machine learning applications.

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