Advancing Weather Image Classification using Deep Convolutional Neural Networks

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***Abstract*—Automatic classification of weather images is a crucial task in the field of meteorology. Recent advancements in Convolutional Neural Networks (CNNs) have demonstrated their effectiveness in image classification. In this paper, we propose an innovative CNN-based approach for weather image classification. Building upon prior research, our model capitalizes on the exceptional feature extraction capabilities of CNNs to accurately classify weather images across various categories. To enhance the generalization performance, we train the model using a combination of data augmentation techniques, including rotation, scaling and flipping. This paper introduces a CNN model specifically made for weather image classification, encompassing categories such as cloudy, sunny, rainy and snowy conditions. Through extensive training and evaluation on a substantial weather image dataset, our proposed model achieves an impressive accuracy rate of 98%. Our experimental results highlight the superior performance of our CNN model when compared to various state-of-the-art methods in weather image classification.**

***Index Terms*—Weather Image Classification, Convolutional Neural Network (CNN), Image Recognition, Machine Learning, Meteorological Data Analysis**

I. Introduction

Weather conditions play a pivotal role in our everyday activities, and precise weather forecasting holds paramount importance for diverse applications such as agriculture, transportation and disaster management. An effective approach to enhance weather forecasting is by analyzing and classifying weather images. However, the classification of weather conditions through image analysis is challenging due to the inherent variability of weather patterns, intricate atmospheric phenomena and diverse imaging conditions [20], [30]. Fortunately, recent advancements in CNNs have showcased exceptional capabilities in image classification tasks, including the classification of weather images [3].

The field of image classification has experienced remarkable growth in recent years, primarily attributed to advancements in computer vision techniques [10], [17], [19], [23]. Among these techniques, CNNs have emerged as a powerful tool, consistently achieving state-of-the-art performance across various domains [25]. Weather image classification is one such domain that has garnered significant attention, owing to its applications in weather forecasting and climate monitoring. By accurately categorizing weather images, valuable insights can be gained to enhance our understanding of weather patterns and facilitate informed decision-making processes.

Weather image classification holds immense significance for multiple reasons. Firstly, it offers valuable insights into weather patterns and atmospheric phenomena, greatly enhancing the accuracy of weather forecasting. By effectively categorizing weather images, we can gain a deeper understanding of the complex dynamics that influence our weather systems.

Secondly, the classification of weather images plays a vital role in identifying hazardous weather conditions, such as thunderstorms, hail or tornadoes. This capability enables the prediction of potential damages and helps in implementing timely precautionary measures to minimize the risk of loss of life and property.

Furthermore, weather image classification contributes to the monitoring of climate change by tracking and analyzing weather patterns over extended periods. By identifying long-term trends and variations, we can better comprehend the impacts of climate change and make informed decisions towards mitigating its effects.

A wide range of approaches has been proposed for weather image classification, encompassing both traditional machine learning and advanced deep learning techniques. Notably, CNNs have emerged as a prominent method in this field, owing to their remarkable capability and potential to learn and extract features from complex images.

CNNs offer a notable advantage by learning features at various levels of abstraction, empowering them to classify images based on their semantic content [31]. This inherent capacity to discern intricate patterns and extract meaningful representations has propelled CNNs to the forefront of weather image classification research. The ability of CNNs to automatically learn hierarchical features from raw image data makes them particularly suitable for handling the intricate and diverse nature of weather images [15], [18], [29].

Despite the notable successes achieved in weather image classification using CNNs, there remains ample room for improvement in this field. One of the primary challenges lies in handling the imbalanced distribution of classes within datasets, where certain weather patterns occur significantly less frequently than others. This class imbalance poses a considerable hurdle, often resulting in poorer performance on the minority classes. Addressing this issue is crucial to ensure comprehensive and accurate classification across all weather patterns.

Furthermore, the generalization of models to new and unseen weather patterns presents another significant challenge. Weather conditions exhibit immense variability, with the emergence of new patterns and atmospheric phenomena.

Overcoming these challenges necessitates novel approaches that specifically tackle class imbalance issues and focus on enhancing the models' ability to generalize to unseen weather patterns. Addressing these concerns will contribute to further advancements in weather image classification, facilitating more accurate and comprehensive analysis of weather conditions.

In this paper, we present a novel CNN-based approach for weather image classification that effectively tackles key challenges associated with this task. Our approach aims to address two critical aspects: class imbalance and limited training data. To overcome the challenge of class imbalance, we adopt strategic techniques in our model design. Additionally, we augment our dataset with synthetic data, which helps to alleviate the scarcity of samples for underrepresented weather patterns. By incorporating synthetic data, we enhance the overall training data distribution and improve the model's ability to accurately classify both common and rare weather patterns.

Through our proposed CNN-based approach, augmented dataset and data augmentation techniques, we aim to improve the accuracy and reliability of weather image classification. The combination of these strategies addresses important challenges associated with this task and contributes to advancements in the field of weather analysis and forecasting.

The rest of the paper is organized as follows. Section II presents an overview of related work in weather image classification, highlighting the existing research in this domain. In Section III, we present our proposed CNN-based approach in detail. This includes a comprehensive description of our dataset, the architectural details of our model, and the training procedures employed. Section IV showcases the experimental results obtained from our approach and provides a comparative analysis against existing methods. Finally, Section V concludes the paper by summarizing the key findings and implications, followed by a discussion on potential avenues for future research in this field.

II. Literature Review

CNNs have emerged as powerful deep learning algorithms renowned for their capability to extract significant image features [26]. This effectiveness is attributed to their deep architecture, utilization of local receptive fields, spatial subsampling and shared weights. CNNs have achieved remarkable success across diverse domains, including face recognition, regression prediction and object detection [12]. Notably, the breakthrough performance of the AlexNet model in the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) has further solidified the prominence of CNNs in image classification tasks [11]. By leveraging their inherent hierarchical structure and feature extraction capabilities, CNNs have paved the way for advancements in numerous applications involving visual data analysis.

In recent years, the application of CNNs has extended into the domain of meteorological studies, showcasing their versatility and effectiveness. Researchers have leveraged CNNs to tackle various weather-related challenges with notable success. For instance, Guo [5] employed deep CNNs to extract snow cover from remote sensing imagery, enabling precise monitoring and analysis of snow patterns. Lu [16] proposed CNN-based architectures specifically designed for cloud recognition, yielding improved accuracy in identifying and classifying different cloud types. These advancements have enhanced our understanding of cloud formations and their implications in weather forecasting.

Furthermore, Dev [2] introduced a lightweight deep learning architecture that seamlessly integrates daytime and nighttime image segmentation, achieving superior results in image recognition tasks. This approach holds promise in capturing and analyzing weather patterns during different periods, thereby enabling comprehensive monitoring and analysis.

Moreover, researchers have delved into the classification performance of CNNs across various weather phenomena. Some investigations have concentrated on two-class weather classification, distinguishing between "sunny" and "cloudy" conditions or three-class classification encompassing "rainy," "foggy" and "snowy" weather [4], [24]. Building upon these studies, other researchers have expanded the classification scope to encompass six distinct weather phenomena, including "dew," "dust," "rain," "frozen," "snow" and "haze." To achieve this, they employed deep learning techniques and utilized three-channel convolutional neural networks (3C-CNN) [28]. These endeavors aimed to recognize weather phenomena by treating it as a multi-label classification task.

However, it is important to note that these studies focused on a limited number of weather categories, failing to encompass the full spectrum of real-life weather phenomena. The field of meteorology entails a considerably broader range of weather patterns and atmospheric conditions. Thus, it becomes crucial to account for a wider variety of weather phenomena when analyzing and recognizing them. By considering a more comprehensive set of weather categories, we can facilitate a more accurate and comprehensive understanding of weather patterns, leading to advancements in meteorological research and applications.

Authors in [8] present a novel approach for weather information retrieval concerning winter precipitation types, employing machine learning techniques. The methodology utilizes data gathered from weather sensors and focuses on forecasting the weather type based on three precipitation classes: rain, freezing rain and snow, as recorded by the Automated Surface Observing System (ASOS). To enable accurate classification, the authors evaluate six supervised machine learning models, namely Naive Bayes, Decision Stump, Hoeffding Tree, HoeffdingOption Tree, HoeffdingAdaptive Tree and OzaBag. These models are selected for their potential in accurately predicting winter precipitation types within the proposed framework.

Presently, significant research efforts are dedicated to the development of accurate forecasting models for weather prediction [22]. Within this context, specific studies focus on investigating the influence of weather conditions on traffic, with particular emphasis on factors like rain and fog [1]. These investigations often utilize real images obtained from cameras situated in natural scenes, such as roads or highways, which offer a unique set of features relevant to driving assistance systems. However, it is essential to acknowledge that these images introduce variations in background and context, potentially impacting the accuracy of weather classification models [21].

The utilization of real-world images in weather classification poses a challenge due to the inherent complexities introduced by the surrounding environment. Variations in lighting conditions, occlusions and diverse backgrounds can affect the performance and robustness of weather classification models. Consequently, it becomes crucial to address these challenges by exploring techniques that enhance the models' ability to generalize across different backgrounds and effectively extract weather-related features.

Machine learning techniques play a pivotal role in extracting significant features from weather images, ultimately enhancing the accuracy of classification models. In this regard, Huang [6] conducted a study aimed at improving image retrieval performance by incorporating texture and color features. The research findings showcased superior performance compared to alternative methods, underscoring the efficacy of leveraging machine learning algorithms to enhance the retrieval and analysis of weather images.

By incorporating texture and color features, the study by Huang [6] demonstrates the potential of integrating additional image characteristics beyond traditional approaches. This broader feature representation enhances the discriminative power of the models and enables more accurate retrieval and classification of weather images. Such advancements contribute to a deeper understanding of weather patterns, ultimately supporting improved forecasting and decision-making processes in meteorological applications.

Recent studies have explored the application of deep learning techniques in various domains, showcasing their potential to enhance accuracy and provide effective solutions. For instance, works [27] focused on Twitter sentiment analysis, specifically analyzing user sentiments in COVID-19-related tweets. These studies employed seven different deep learning models based on LSTM neural networks to classify sentiment. In a similar vein, the work in [7] emphasized the significance of utilizing up-to-date methods in the aviation industry, further highlighting the versatility and advancements of diverse techniques across different domains. These references collectively demonstrate the continuous development and wide-ranging applications of deep learning, contributing to the creation of robust and efficient solutions.

Future studies can focus on several areas to advance the field of weather classification. Firstly, exploring novel feature extraction techniques that capture intricate patterns and subtle variations in weather images can enhance the discriminative power of classification models. Additionally, considering the integration of multi-modal data sources, such as satellite imagery, radar data and environmental sensors, can provide a more comprehensive understanding of weather patterns and improve prediction accuracy.

Finally, this research will contribute to improved decision-making processes and better preparedness in various domains that rely on accurate weather predictions, such as agriculture, transportation and disaster management.

III. Model

The main objective of this research paper is to investigate different deep learning approaches that combine principles of artificial intelligence with image classification techniques for weather image classification. Several architectures of deep neural networks have been examined, with a specific emphasis on (CNNs) due to their exceptional performance in handling image data [9].

The proposed models consist of three distinct architectures, each initially implemented using different configurations before converging to the same final design. The architectural differentiations among these networks are summarized in Table I. All three networks incorporate common layers such as GlobalAveragePooling2D, Flatten, Dense(256) and Dropout.

TABLE I
ARCHITECTURES

Number	Architecture
1st	(Conv2D - MaxPooling2D) $\times 3$
2nd	(Conv2D $\times 2$ - MaxPooling2D) $\times 3$
3rd	(Conv2D $\times 3$ - MaxPooling2D) $\times 3$

IV. Evaluation

A. Dataset

The dataset[1] has 6-folders: 5-folders possessing each type of pictures and also one along with the alien-test possessing the images of all groups. It also consist a csv file having the labels for the images in alien-test file.

[1]https://www.kaggle.com/datasets/vijaygiitk/multiclass-weather-dataset

The dataset includes 5 various classes of climate picked up from the above claimed different resources, however it's real world records so any type of unit for weather distinction must have the ability to handle this sort of photos. The dataset includes regarding 1500 tagged images featuring the recognition graphics. Images are not of dealt with measurements and the photos are actually of different sizes. Each image has just one weather condition group and are spared in separate file since the classified class. Each picture have been measured for the weather condition on a scale of 0 to 4: 0 - Cloudy, 1 - Foggy, 2 - Rainy, 3 - Shine, 4 - Sunrise as it appears in Table II. In order to create a balanced learning model, the images had to be balanced. Therefore the number of images exists in Table III.

TABLE II
WEATHER CATEGORY

0 - Cloudy 1 - Foggy 2 - Rainy 3 - Shine 4 - Sunrise

TABLE III
DISTRIBUTION OF CLASS INSTANCES - DATASET MASTER

Alien-Test	Cloudy	Foggy	Rainy	Shine	Sunrise
30	300	300	300	250	350

B. Results and Analysis

In this subsection, the speculative assessment is recommended. Specifically, Table IV and Figure 1 offer the results for the 3 designs in regards to epochs, accuracy, loss as well as time.

In the first architecture with batch size 128, the loss starts at 1.409 and reaches 0.0549 by the end of training. The accuracy for the validation set starts at 39% and gradually increases to a maximum of 98% during training. The training time for each epoch is around 5 seconds. As the batch size increases to 256, the loss starts at 1.523 and reaches 0.2033, while the accuracy starts at 37% and reaches 93% by the end of training. The training time per epoch remains similar to the previous architecture. For batch size 512, the loss starts at 1.599 and reaches 0.4156, with the accuracy starting at 22% and reaching 84% at the end of training. The training time per epoch is still around 5 seconds. Finally, with batch size 1024, the loss starts at 1.613 and reaches 0.6275, while the accuracy starts at 17% and reaches 75% by the end of training. The training time per epoch is 6 seconds.

Moving on to the second architecture, with batch size 128, the loss starts at 1.548 and reaches 0.1834, while the accuracy starts at 34% and reaches 93% by the end of training. The training time per epoch is longer than the first architecture, around 13 seconds. For batch size 256, the loss starts at 1.598 and reaches 0.4303, with the accuracy starting at 22% and reaching 82% at the end of training. The training time per epoch is 13 seconds as well. As the batch size increases to 512, the loss starts at 1.601 and reaches 0.6245, while the accuracy starts at 29% and reaches 76% by the end of training. The training time per epoch is longer, around 14 seconds. Finally, with batch size 1024, the loss starts at 1.607 and reaches 0.8389, with the accuracy starting at 24% and reaching 65% by the end of training. The training time per epoch is 15 seconds.

In the third architecture, with batch size 128, the loss starts at 1.539 and reaches 0.4064, while the accuracy starts at 22% and reaches 86% at the end of training. The training time per epoch is around 15 seconds. For batch size 256, the loss starts at 1.602 and reaches 0.6558, with the accuracy starting at 28% and reaching 72% by the end of training. The training time per epoch remains at 15 seconds. As the batch size increases to 512, the loss starts at 1.608 and reaches 0.8215, while the accuracy starts at 25% and reaches 64% by the end of training. The training time per epoch is around 16 seconds. Finally, with batch size 1024, the loss starts at 1.609 and reaches 0.8339, with the accuracy starting at 20% and reaching 63% by the end of training. The training time per epoch is around 16 seconds.

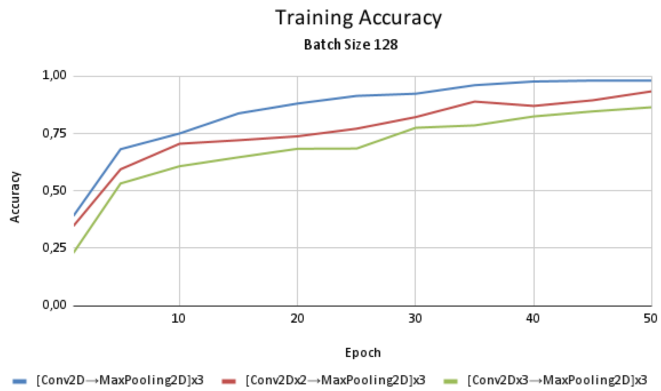
In summary, the first architecture shows the best performance in terms of accuracy, reaching up to 98% for the validation set. The second and third architectures have lower accuracy but still show improvement throughout the training process.

V. CONCLUSIONS AND FUTURE SCOPE

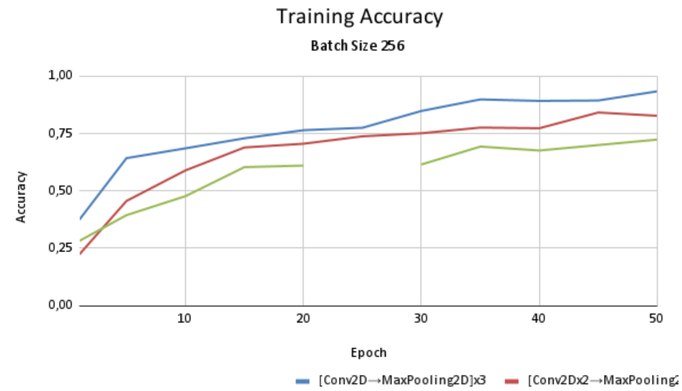
In this research paper, we introduced a set of methodologies to develop a convolutional neural network (CNN) for multiclass weather image classification. The utilization of CNNs, known for their effectiveness in processing image data, was the core focus of these techniques. We evaluated the performance of each architecture using various batch sizes, including 128, 256, 512 and 1024.

To further improve accuracy, it is recommended to explore and experiment with different models and combinations proposed in this study. Additionally, conducting tests on larger datasets can contribute to additional enhancements in classifier performance. By expanding the dataset, the model can learn from a wider range of examples and improve its generalization abilities. Further research can also investigate the impact of hyperparameter tuning, data augmentation techniques, and incorporating transfer learning to achieve even better results in weather image classification tasks.

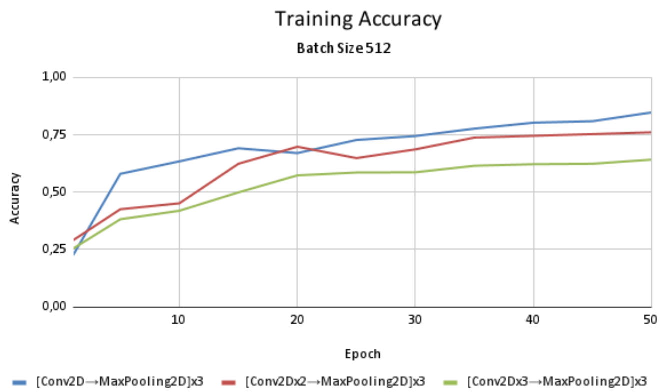
An additional avenue for future research could involve the integration of semi-supervised learning algorithms, which have emerged as a prominent research area offering an alternative to conventional classification methods. These algorithms leverage both labeled and unlabeled data, combining the explicit classification information from labeled instances with the latent knowledge embedded in unlabeled data. By harnessing this unlabeled data, powerful and effective classifiers can be constructed. The works in [14], [13] serve as examples of such an approach and underscore the potential benefits and advancements that can be achieved by incorporating semi-supervised learning techniques into the field of classification.



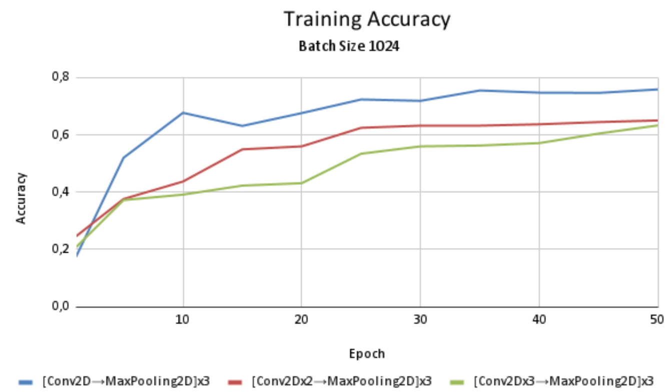
(a) Batch Size = 128



(b) Batch Size = 256



(c) Batch Size = 512



(d) Batch Size = 1024

Fig. 1. Accuracy for different batch sizes for the three proposed models

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TABLE IV
EXPERIMENTAL EVALUATION FOR THREE ARCHITECTURES

Epochs	Loss	Accuracy	Time	Loss	Accuracy	Time	Loss	Accuracy	Time	Loss	Accuracy	Time
1st: (Conv2D - MaxPooling2D) $\times 3$												
	Batch Size = 128			**Batch Size = 256**			**Batch Size = 512**			**Batch Size = 1024**		
1	1.409	0.3905	5	1.523	0.3743	5	1.599	0.2257	5	1.613	0.1743	6
5	0.8076	0.6819	6	0.9254	0.6429	4	1.040	0.5800	4	1.136	0.5200	6
10	0.6170	0.7505	4	0.7628	0.6857	4	0.8892	0.6343	5	0.8833	0.6771	4
15	0.4354	0.8381	5	0.6856	0.7295	4	0.8116	0.6914	4	0.8911	0.6314	6
20	0.3180	0.8810	4	0.5890	0.7648	4	0.8282	0.6705	6	0.8159	0.6762	4
25	0.2331	0.9143	5	0.6054	0.7752	4	0.6805	0.7276	4	0.7385	0.7238	6
30	0.2065	0.9238	4	0.4159	0.8486	5	0.6570	0.7448	6	0.7296	0.7190	4
35	0.1214	0.9610	4	0.2991	0.8990	4	0.6012	0.7771	4	0.6473	0.7552	5
40	0.0900	0.9771	4	0.2994	0.8924	5	0.5108	0.8029	6	0.6365	0.7476	4
45	0.0550	0.9810	4	0.3122	0.8943	4	0.4792	0.8095	4	0.6246	0.7467	4
50	0.0549	0.9810	4	0.2033	0.9343	5	0.4156	0.8476	6	0.6275	0.7590	5
2nd: (Conv2D $\times 2$ - MaxPooling2D) $\times 3$												
	Batch Size = 128			**Batch Size = 256**			**Batch Size = 512**			**Batch Size = 1024**		
1	1.548	0.3467	13	1.598	0.2229	13	1.601	0.2905	14	1.607	0.2457	15
5	1.001	0.5943	11	1.235	0.4562	9	1.190	0.4257	12	1.283	0.3762	11
10	0.7602	0.7057	9	0.9863	0.5895	11	1.150	0.4514	12	1.127	0.4371	9
15	0.7242	0.7210	11	0.7813	0.6895	11	0.9118	0.6238	10	1.048	0.5495	11
20	0.6567	0.7381	11	0.7465	0.7057	11	0.8020	0.6981	11	0.9774	0.5600	9
25	0.5878	0.7714	11	0.6641	0.7381	11	0.8891	0.6486	12	0.9704	0.6248	11
30	0.4965	0.8219	11	0.6532	0.7514	10	0.8250	0.6867	12	0.9378	0.6324	9
35	0.3103	0.8895	10	0.5756	0.7762	11	0.7051	0.7381	9	0.8261	0.6324	11
40	0.3795	0.8705	11	0.5439	0.7733	9	0.6618	0.7457	12	0.8385	0.6371	10
45	0.2811	0.8952	9	0.4327	0.8419	11	0.6510	0.7533	12	0.8269	0.6448	11
50	0.1834	0.9343	11	0.4303	0.8276	10	0.6245	0.7610	10	0.8389	0.6505	10
3rd: (Conv2D $\times 3$ - MaxPooling2D) $\times 3$												
	Batch Size = 128			**Batch Size = 256**			**Batch Size = 512**			**Batch Size = 1024**		
1	1.539	0.2295	17	1.602	0.2819	19	1.608	0.2543	18	1.609	0.2076	19
5	1.089	0.5324	15	1.220	0.3943	15	1.459	0.3819	16	1.391	0.3724	15
10	0.8893	0.6076	15	1.118	0.4771	15	1.208	0.4190	16	1.210	0.3914	15
15	0.8411	0.6467	15	0.9554	0.6038	15	1.151	0.4990	16	1.126	0.4229	16
20	0.7223	0.6838	15	0.9121	0.6105	15	0.9949	0.5733	16	1.122	0.4314	16
25	0.7636	0.6848	16	0.8504	0.6286	15	0.9520	0.5857	16	1.051	0.5343	16
30	0.6227	0.7752	16	0.8156	0.6152	15	0.9048	0.5867	16	1.032	0.5600	16
35	0.5881	0.7857	15	0.7300	0.6933	15	0.8625	0.6152	16	0.9170	0.5629	16
40	0.4870	0.8248	15	0.7630	0.6762	16	0.9051	0.6219	16	0.9130	0.5714	15
45	0.4213	0.8467	16	0.7034	0.7000	15	0.9635	0.6238	16	0.8974	0.6048	16
50	0.4064	0.8648	16	0.6558	0.7238	15	0.8215	0.6419	16	0.8339	0.6333	15

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