A study on using generative deep learning architectures for classification of ground-based cloud images

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Outline

1. Introduction
2. Motivation
3. Related work
4. Research contribution
   - Proposal
   - Diffusion model
   - Vision Transformer
   - Case study on real data
5. Discussion
6. Conclusions and future work

Introduction

Context and importance

- Weather and climate change play a crucial role in society.
- Extreme weather events, predominantly caused by climate change, affect all everyday activities.
- Weather forecasting is essential for preventing large-scale disasters.
- Identification and prediction of severe weather phenomena is difficult.

Introduction (2)

Clouds classification

- There are various classifications for the clouds.
- The standard set is considered to be the WMO's [WMO]:
  - High clouds: **Cirrus** (Ci), **Cirrocumulus** (Cc), **Cirrostratus** (Cs);
  - Middle clouds: **Altocumulus** (Ac), **Altostratus** (As), **Nimbostratus** (Ns);
  - Low clouds: **Stratocumulus** (Sc), **Stratus** (St), **Cumulus** (Cu), **Cumulonimbus** (Cb).

Introduction (3)

Figure: Cumulus clouds [WMO]

Motivation

- Clouds display many characteristics (e.g., colour, shape) which are not easily quantifiable.
- **Cloud identification** represents one of the main activities of the weather stations personnel.
- Much data collected by satellites and instruments can be processed automatically.
- A relatively new topic in AI with much potential. *Machine Learning* proves to be a promising domain.

Motivation (2)

Figure: A tropical cyclone [WMO]

Related work

Details

- There is a progression from traditional image processing techniques toward more complex neural models.
- The approaches vary:
    - **supervised**
    - **unsupervised**
    - **self-supervised**
- **Public datasets involved:** Cirrus Cumulus Stratus Nimbus (CCSN) [Liu19], Ground-based Cloud Dataset (GCD) [LDZ+22], SWIMCAT, MODIS, LSCIDMR.

Related work (2)

- **Zhang et al. [ZLZS18]** introduced **CloudNet**, a CNN inspired by AlexNet, trained on the CCSN dataset with 11 cloud classes. Achieved 88% accuracy (CCSN) and 98.6% (SWIMCAT).
- **Mihuleț et al. [MC25]** proposed **X-Cloud** and **M-Cloud**, lightweight CNNs based on Xception, trained on CCSN and GCD datasets. Achieved 75% average accuracy with high efficiency.
- **Luo et al. [LPS+24]** developed a YOLOv8-based pipeline with haze-reduction preprocessing and image segmentation. Trained on 4000-image Tibet dataset, achieving near-perfect training accuracy.

Related work (3)

- **Yousaf et al. [YRK+23]** used over 100k satellite images (LSCIDMR), proposing a CNN-ResNet model inspired by VGGNet. Achieved 97.25% accuracy using GAP and softmax classification.
- **Togaçar et al. [TE22a]** implemented a mobile-friendly ShuffleNet with super-resolution, semantic segmentation, and SFO feature selection. Best accuracy: 98.56% using LDA.
- **Dev et al. [DLW15]** proposed a texton-based model using S-filters and k-means clustering, tested on SWIMCAT. Achieved near-perfect classification, struggling slightly with veil clouds.

Related work (4)

- **Vasylieva et al. [VM22]** trained a CNN on NOAA-20 satellite imagery for 4-class cloud classification. Achieved 95% training and 85% validation accuracy.
- **Geiss et al. [GCV+24]** proposed a self-supervised SNN with Barlow Twins loss. Trained on MODIS and ABI datasets, outperforming supervised models with accuracy surpassing 80%.
- **Kurihana et al. [KKF+19]** used a deep CAE with advanced loss metrics and HAC clustering on MODIS data. Showed good unsupervised class separation and high AMI stability scores.

GCD dataset peek

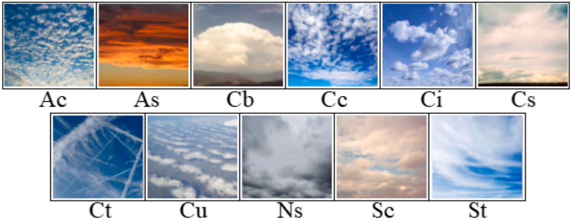


Figure: Sample images extracted from CCSN dataset [TE22b]

Proposal

- Proposed ideas reside at the intersection of generative models and transformer-based architectures.
- Enhancing the performance of cloud classification from images using a **Diffusion (Classifier)** and a **Vision Transformer** (ViT), both of which provide notable benefits:
  - contextual reasoning using mechanisms such as *attention*;
  - generative capabilities that enhance *generalization* and analyse small details.

Diffusion classifier (1)

- Learn a bijection between original domain and pure noise space.

- Consists of two steps: forward and **reverse diffusion** processes for altering an image.
  - the formulation of the forward process function:

$$q(x_t|x_{t-1}) = N(x_t, \sqrt{1-\beta_t}x_{t-1}, \beta_t I) \quad (1)$$

- x_{t-1} and x_t are the input and output at step t
- N is the normal distribution
- β_t is the noise degree scheduler.

Diffusion classifier (2)

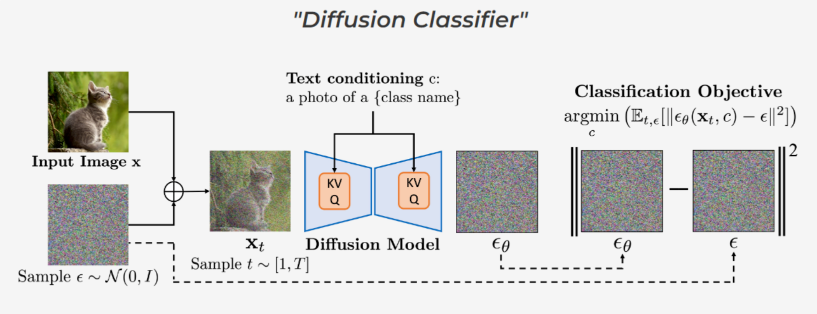
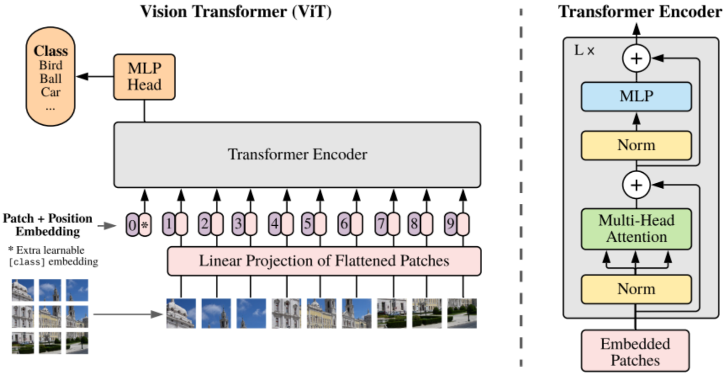


Figure: An overview of the diffusion classifier model [LPD+23]

Vision Transformer (1)

- Complex type of Deep Neural Networks (DNN) that rely on the mechanism of attention.
- Adjusted for image processing, as opposed to regular transformers.
- Techniques involved:
  - Patch Embeddings
  - Positional Embedding
  - Multi-Head Self-Attention

Vision Transformer (2)



Case study on real data

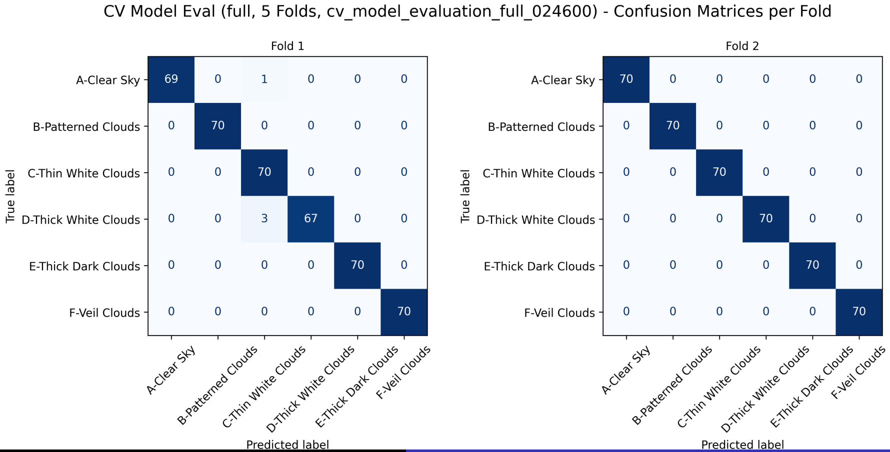
- Further testing is currently in progress, we evaluate multiple models (simple ViT model, hybrid ViT+efficient CNN feature extractor pre-trained on Image-Net).
- At this state, accuracy reached considerable values for some datasets (over 99% on Swimcat-extend, as well as all the other measured metrics.
- This shows the model's well performance and robustness.

Case study results

	Metric	Mean	Std Dev	SEM	CI Margin	CI Lower	CI Upper
1	Accuracy	0.9929	0.0045	0.0020	0.0055	0.9873	0.9984
2	F1 Macro	0.9929	0.0045	0.0020	0.0055	0.9873	0.9984
3	Precision Macro	0.9931	0.0042	0.0019	0.0053	0.9878	0.9984
4	Recall Macro	0.9929	0.0045	0.0020	0.0055	0.9873	0.9984
5	Specificity Macro	0.9986	0.0009	0.0004	0.0011	0.9975	0.9997
6	Roc Auc Macro	0.9997	0.0002	0.0001	0.0003	0.9994	1.0000
7	Pr Auc Macro	0.9930	0.0010	0.0004	0.0012	0.9917	0.9942

Figure: Classification performance of the ViT model on Swimcat-extend (5-Fold CV)

Case study results



Discussion

- CNN-based models (e.g., CloudNet [ZLZS18], ResNet-VGG [YRK+23]) achieve high accuracy (∼98.6%) on balanced datasets using strong augmentation.
- Lightweight architectures (e.g., X-Cloud, M-Cloud [MC25]) prioritize efficiency, trading off accuracy (∼75%) for deployment flexibility.
- Preprocessing-heavy pipelines [LPS+24] improve image quality (e.g., haze correction), but often suffer from limited generalizability due to geographic bias.
- Our ViT model achieved 99% accuracy, validating the value of attention-based mechanisms in capturing complex cloud patterns, while also indicating strong potential for scaling.

Discussion (2)

Approach	Dataset(s)	Classes	Accuracy (%)
CloudNet	CCSN, SWIMCAT	11	88.0 / 98.6
ResNet-VGG	LSCIDMR	11	97.25
X-Cloud / M-Cloud	CCSN, GCD	11, 7	75.0
YOLOv8 + Segmentation	Custom (Tibet)	4	~100 (train), low on Cu
ShuffleNet + SFO	CCSN, SWIMCAT-Ext	11, 6	98.56
CNN	NOAA-20 VIIRS	4	95 (train), 85 (val)
Texton + S-Filters	SWIMCAT	5	~ 100
SNN	MODIS, ABI	Self-supervised	>80
CAE + HAC	MODIS	Unsupervised	N/A
ViT (Ours)	Swimcat	6	**99.0**

Table: Summary of cloud classification models, datasets used, number of classes, and reported accuracies.

Conclusion

- Deep learning has transformed cloud classification, with CNNs and ViTs excelling in capturing visual patterns and contextual dependencies.
- This ViT and Diffusion design addresses key challenges such as class imbalance, image noise, and the difficulty of labelling large datasets.
- These innovations contribute toward automating weather phenomenon analysis, an increasingly vital task in climate-aware societies.

Future Work

- Implement a Diffusion Classifier with similar goals.
- Integrate ViT and Diffusion models into hybrid systems, leveraging both contextual understanding and generative capabilities.
- Investigate multimodal fusion of satellite, radar, and ground-based imagery for richer data representations.
- Utilize generative learning for other tasks such as weather event simulation and prediction.

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