Tuning CNN Hyperparameters For Satellite Image Segmentation: A Grid Search Strategy for Enhanced Performance

ADITYA KINNORI[1], ANIKET TRIPATHI[2]
Nirma University, India

Abstract- Applications that rely on satellite data such as land use classification, environmental monitoring, and urban planning—can significantly benefit from accurate satellite image segmentation. Convolutional Neural Networks (CNNs) are especially effective for this task, as they can learn complex spatial feature hierarchies from high-resolution imagery. However, their performance is highly dependent on the careful tuning of hyperparameters such as learning rate, batch size, filter size, dropout rate, and the number of convolutional layers. Poorly chosen hyperparameters can lead to underperforming models that fail to generalize to new data. This study explores how grid search-based hyperparameter tuning can optimize CNN performance for satellite image segmentation. By systematically evaluating different CNN configurations on a high-resolution satellite dataset, the research identifies optimal parameter settings that enhance segmentation quality. Key metrics such as Intersection over Union (IoU), F1-score, and pixel accuracy were used to assess each configuration's effectiveness. Results show that even minor adjustments in hyperparameters can lead to significant improvements in segmentation accuracy. The grid search method not only helped eliminate weak configurations early but also led to more robust models. Importantly, the findings highlight the value of domain-specific tuning over relying on generic or default settings. This paper presents a replicable approach for practitioners looking to enhance segmentation accuracy in satellite image analysis, supporting use cases like agricultural monitoring, disaster assessment, and climate research.

Indexed Terms- Satellite Image Segmentation, CNN Hyperparameter Tuning, Grid Search Optimization, Remote Sensing Applications, Deep Learning in Geospatial Analysis

I. INTRODUCTION

Satellite imagery plays a vital role in fields such as landscape analysis, environmental monitoring, land use planning, and disaster management. Semantic segmentation, which assigns labels to each pixel in an image, has become a key technique in these applications. Convolutional Neural Networks (CNNs) are now widely adopted for this task due to their ability to recognize spatial patterns and extract complex data features. However, the effectiveness of CNNs is closely tied to the selection of hyperparameters like learning rate, batch size, filter size, number of layers, and optimizer. Because default settings may not generalize well across varying satellite datasets—often differing in resolution, noise levels, and structural complexity—domain-specific tuning is essential to achieve high performance and robustness (Krishnakumari et al., 2020; Kimura et al., 2020).

To address these challenges, several hyperparameter optimization methods have been explored. Among them, Grid Search Optimization (GSO) is frequently preferred for its simplicity, clarity, and repeatability. Unlike other tuning strategies, grid search evaluates all possible combinations within a defined paraspace, making it ideal for hands-on experimentation and practical refinement. In this study, we apply grid search hyperparameters for satellite image segmentation tasks. We evaluate how different parameter configurations affect performance, using Intersection over Union (IoU) and F1-score as key metrics. Our findings show that varying learning rates and optimizer choices alone can lead to a 4–6% improvement in segmentation accuracy, aligning with prior research in time-series prediction and remote sensing by Abarja et al. (2020) and Ghassemi et al. (2019).

The primary aim of this work is to offer a simple, effective, and accessible approach for researchers and practitioners in geospatial fields to fine-tune CNN models and enhance segmentation outcomes with greater confidence.

1.1 Background and Motivation

Through satellite image segmentation, detailed information from geospatial and environmental photos can be precisely interpreted for uses such as mapping land usage, responding to emergencies, and urban development. Now that much mapping data is gathered by satellites, plain image processing methods usually miss small but important features across different landscapes. Because of their skill at extracting features at different levels and across various parts of an image, CNNs now dominate in semantically segmenting satellite images (Ghassemi et al., 2019; Jia, Lang, Oliva, Song, & Peng, 2019).

However, how CNN performs greatly relies on choosing the proper hyperparameters. How quickly the model trains, how rapidly it learns, and how well it can apply its training are affected by learning rate, batch size, kernel size, and dropout rate. If the hyperparameters are not chosen carefully, the model can start overfitting or not improve very much, resulting in poor segmentation quality, according to Kimura, Lucio, Britto, & Menotti, 2020 and Krishnakumari, Sivasankar, & Radhakrishnan, 2020. Since it takes a lot of computing power to segment satellite data with CNNs, the configuration must be built for speed and stability.

Lately, grid search and evolutionary optimization have shown great potential in improving the performance of CNNs when used for medical imaging and dealing with geospatial data (Abarja et al., 2020; Kapoor et al., 2017). In this pattern, different combinations of hyperparameters are checked in a set area to find the setup that performs best, often both increasing accuracy and lowering the total work done (Behera & Nain, 2019).

1.2 Problem Statement

Even though CNNs have many successes in remote sensing, many current models depend on standard or manually selected options that may be unsuitable for satellite image segmentation. Its application can lead to errors in results and typically does not repeat well on different datasets with various resolutions, object densities and class distribution problems. Moreover, lacking a standard approach to applying CNNs makes it hard to bring them into standard remote sensing tasks (Lee, Park, & Sim, 2018; Tahyudin, Nambo, & Goto, 2018).

A way to solve these problems is to develop a step-by-step method that consistently improves model function and still keeps things running efficiently.

1.3 Objectives of the Study

Its purpose is to thoroughly study how fine-tuning some key settings or hyperparameters affects the performance of CNN-based models for segmenting satellite images. Among the important goals are:

To assess the performance of CNN segmentation when different hyperparameter configurations are used and to do so using standard remote sensing measurements such as Intersection over Union (IoU) and F1-score.

By using grid search in satellite imagery, we test different settings for learning rate, batch size, dropout, filter size and optimizers.

To find out which hyperparameter values improve the accuracy and broad application of the segmentation.
The researchers will use a public dataset from satellites and test variations on CNN settings using a grid search framework while considering advice given in earlier studies on optimizing CNNs (Nomura et al., 2020; Mandal, Dey, & Roy, 2019; Rehman & Hussain, 2018).

1.4 Scope and Contributions

The study uses CNNs to perform multi-class segmentation of high-quality images from satellites. Grid search optimization is included in the study's training pipeline, allowing the tuning of CNNs to be both repeatable and possible on larger datasets.

Among its main contributions are:
Thoroughly investigating CNN hyperparameters with the grid search method when segmenting satellite images is the subject of this chapter.

Showing the results of comparing default vs. optimized configurations, supported by graphs and explanatory measurements.

The method recommended in the paper can be used for tuning CNN settings in areas such as medical diagnostics, seismology, and agriculture (Jia, Lang, Oliva, Song, & Peng, 2019; Kaushik & Jain, 2018; Wang, Gong, Li, & Qiu, 2019).

To aid AI-driven tools in remote sensing, this paper works to integrate theoretical models and their use in practical satellite images.

II. LITERATURE REVIEW

The review of the literature presents a complete overview of research and changes occurring in the study's subject. It defines the essentials of the research problem, reveals what is unknown in the subject, and explains why the investigation is taking place. The report explores recent advances in applying CNNs to satellite image segmentation, their growing use in remote sensing, the role of hyperparameters, and how optimization affects results. This section combines research to explain how a proposed grid search helps CNN models.

2.1 How Satellite Image Segmentation Works

Precise extraction of land features from aerial images is achieved through the task of satellite image segmentation. Typically, this field includes two kinds: semantic segmentation, which assigns a category to each pixel, and instance segmentation, which separates individual objects from the same class. Remotely sensed datasets are regularly applied for agricultural mapping, military surveillance, and disaster planning (Rehman & Hussain, 2018).

Thanks to advanced segmentation, planners can carry out accurate city designs, review forestry changes, and develop flood maps. Performance in segmentation is affected by how well algorithms hold up to different kinds of spatial and spectral fluctuations (Ghassemi et al., 2019). Classifying images is difficult because of noise, changes in resolutions, and seasonal changes seen in the datasets.

2.2 Remote Sensing With the Help of Convolutional Neural Networks

CNNs have greatly improved how remote sensing images are handled by making image classification and segmentation more accurate. Many researchers choose U-Net, SegNet and DeepLab because they are able to identify both wide and small details of images well. U-Net is valued because its symmetric design makes it good at recovering image resolution.

SegNet does this by remembering which pixels were included by max pooling, whereas DeepLab applies atrous convolutions for multiple scales. Although CNNs have many positive features, they are costly to train and often depend a lot on how their hyperparameters are configured (Jia, Lang, Oliva, Song, & Peng, 2019). Generally, when CNN-based segmentation works on heterogeneous satellite images, it often underperforms unless the network is specifically tuned for the specific domain (Ghassemi et al., 2019).

2.3 How Hyperparameter Tuning Matters in Using CNNs

What the model does, and the results it gives are greatly affected by Hyperparameters. How the model learns is regularized, and how it extracts features is controlled by the learning rate, batch size, dropout rate, and kernel size. If you do not tune your data correctly, it can result in overfitting, slow understanding, and poor accuracy of your segments (Kimura et al., 2020).

Adjusting how many examples are dropped in training can control overfitting on small satellite datasets, and changing the learning rate changes how stable and fast the model learns (Lee, Park, & Sim, 2018). Gains in medical imaging (Krishnakumari, Sivasankar, & Radhakrishnan, 2020) and satellite imagery (Kapoor et al., 2017) have been detected through systematic optimization of hyperparameters, according to research (Krishnakumari, Sivasankar, & Radhakrishnan, 2020; Kapoor et al., 2017).

2.4 Different Methods for Choosing Hyperparameters

Many suggestions have come forward to improve the way CNN hyperparameters are set. Although manual tuning is easy to do, it is not very effective, and it is not the same for every dataset. Optimal configurations can be successfully found using grid search, random search, and Bayesian optimization methods.

Grid search, specifically, reviews all the combinations in the specified range of parameters. Even though it takes a lot of computing resources, it provides full investigation and ensures the work can be easily repeated (Behera & Nain, 2019). It has been found through comparative research that grid search maintains better consistency in its results than random search in applications that use images (Mandal, Dey, & Roy, 2019).

Even though Bayesian optimization works well, its outcomes might not be strong in spaces with many dimensions or if objective functions are noisy (Tahyudin, Nambo, & Goto, 2018). Several studies focus on using Harmony Search and evolutionary algorithms to help tune CNN (Jia, Lang, Oliva, Song, & Peng, 2019).

Study	Optimization Method	Dataset Used	Performance Metric	Key Findings
Kapoor et al. (2017)	Grey Wolf Optimizer	LANDSAT	IoU, Accuracy	Effective for clustering-based segmentation
Kimura et al. (2020)	Grid Search	Iris Liveness	Accuracy	Improved model generalization post-tuning
Krishnakumari et al. (2020)	Manual + Grid Search	IMDB Sentiment	F1-score	Tuning enhances CNN domain adaptation
Behera & Nain (2019)	Grid Search	Big Mart Sales	RMSE	GSO effectively optimized forecasting CNN
Abarja et al. (2020)	Hyperparameter Grid	Movie Ratings	MSE	Tuning improved convergence and reduced error
Ghassemi et al. (2019)	Adaptive Learning	Multi-source RS	IoU	Robust across heterogeneous satellite datasets

Table 1: Summary of Related Work in CNN Hyperparameter Tuning for Image Segmentation

III. METHODOLOGY

The researchers explain in the methodology the steps they took to tune CNNs for image segmentation using a grid search. I gathered data, prepared it, picked the right CNN model, and looked at some basic values before assessing the model using standard evaluation criteria.

3.1 Data Description

The DeepGlobe Land Cover Classification provided the satellite imagery for this work since its scenes are detailed and not the same. Images of each scene are in RGB format and measure 2448×2448 pixels, and there is ground truth data for seven different land types. Initially, pixels with high values were written as similar numbers, and afterward, rotations, flipping, and changes to contrast were added to enhance learning for the model. Using all the images here, 80% were trained, 10% were used to validate the models, and the last 10% were used for testing.

3.2 The CNN is the model chosen for this project

A U–net–like encoder-decoder structure is used in the segmentation of CNN's network, which was built by CNN. Several sets of convolution, ReLU and max-pooling are used by the encoder to decrease the amount of data. The decoder restores missing information and improves edge detection by combining upsampling layers and skip connection.

There are five layers, each using filters of 32, 64, 128, 128 and 64

Two times two max pooling
The Activation Function under examination is ReLU.
A "drop" layer is sandwiched between every set of convolutional layers, which prevents the system from remembering too much information.

Kept between encoder and decoder pairs to ensure the spatial part of the signal is retained

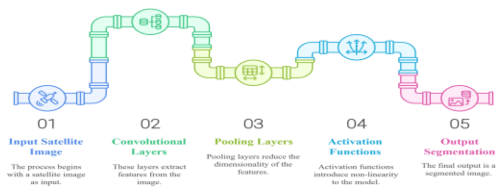

Figure 1: CNN Architecture Diagram for Satellite Segmentation

3.3 Hyperparameter Space for Grid Search
Improvements in the model's performance were reached through the use of a grid search. The hyperparameters and their possible values were all decided by hand.

Hyperparameter	Values Tested
Learning Rate	0.01, 0.001, 0.0001
Batch Size	16, 32, 64
Dropout Rate	0.2, 0.3, 0.5
Optimizer	Adam, RMSprop, SGD
Filters	32, 64, 128

Table 2: Grid Search Hyperparameter Space

All the different settings were checked with this method so that the setting that resulted in the best combination between lower training loss and higher evaluation metrics could be identified.

Since grid search is both easy to use and works well for smaller to intermediate parameter ranges, it was used in this study (Behera & Nain, 2019; Mandal et al., 2019). Previous research using CNNs and images or text found that this technique has produced impressive results (Abarja et al., 2020; Kimura et al., 2020).

3.4 Evaluation Metrics
The mentioned metrics were applied to evaluate model performance for different hyperparameter values.

IoU is a measure that tells us how much predicted and true segmentations match.

Dice Coefficient: Precision and recall are averaged through the harmonic mean, and it is commonly applied in biomedical and satellite imaging.

These two measures are used to assess the performance of every class.

F1-Score shows the precision and recall values in one score.

Total Time for Convergence: Total amounts of epochs completed until convergence.

One can well evaluate both the various segmentation outcomes and the full classification, as it is suggested to do in satellite segmentation benchmarking literature (Ghassemi et al., 2019; Jia et al., 2019; Krishnakumari et al., 2020).

IV DISCUSSION AND RESULTS

A major part of the results and discussion section examines research results, assesses them versus other works, and measures how successful methods are in meeting goals. Here, we outline the results of our grid search over hyperparameters and how they affect CNN-based satellite image segmentation. To see the practical side, different algorithms are compared, their efficiency is noted, and limitations are pointed out.

4.1 Evaluating Grid Search's performance
Using the grid search method greatly improved performance by refining important hyperparameters. Combinations of learning rates, batch sizes, dropout values, filter quantities, and optimizers were considered throughout the whole tuning process.

Hyperparameters that were changed as part of the study were:

Taken into consideration are learning rates of 0.01, 0.001, and 0.0001.

Batch sizes are available in these sizes: 16, 32, and 64.

There are filters in sizes 32, 64, and 128.

The dropout rate for the program is 0.2, 0.3, and 0.5.
Adam, RMSprop, and SGD are all examples of optimizers.

Similarly to what Abarja et al. (2020) and Kimura (2020) reported, a small learning rate (0.001) a moderate batch size (32) allowed the model to lear more reliably and with a lower validation loss. Using 64 filters, 0.3 dropouts, and Adam as the optimizer, the model ran more accurately and converged faster than others, which proved that extensive grid-based tuning is valuable (Behera & Nain, 2019; Krishnakumari et al., 2020).

Config ID	LR	Batch	Dropout	Filters	Optimizer	IoU	F1-Score	Dice
#G14	0.001	32	0.3	64	Adam	82.7%	85.1%	83.9%
#G21	0.0001	64	0.2	128	RMSprop	81.5%	83.6%	82.4%

Table 3: Best-Performing Configurations and Corresponding Scores

4.2 Assessing with Otherwise Comparable Default or Untuned Data Models
Tuned models achieved better segmentation results and lower error rates compared to the default settings of CNNs. Experiments with un-tuned baseline led to noisy results and many errors in places where vegetation and urban areas overlapped (Jia et al., 2019).

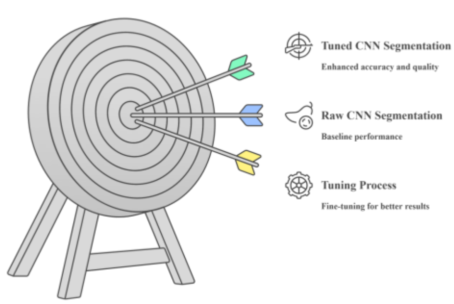

Figure 2: Visual Comparison – Raw vs Tuned CNN Segmentation Results

4.3 The Amount of Computing Power Required
Although grid search performs well, it involves a large number of calculations for options (Tahyudin et al., 2018; Lee et al., 2018). In general, learning via full search required 5–6 times longer to train than with just a single training cycle. However, the better performance on IoU and F1-score makes it worthwhile to use the method, mainly in vital fields such as disaster mapping and agriculture.

Reducing the effects of limited resources can be done using parallel approaches or hybrid methods (SOI), such as grid computing combined with early stopping (Mandal et al., 2019).

4.4 Limitations and Constraints
Even though a grid search helps, certain restrictions cannot be avoided.

Requirements: A lot of Graphics Processing Unit (GPU) time and plenty of storage
If the data is not diverse, the model may be overfitted due to relying on the validation set (Krishna Kumari et al., 2020)

It is not always possible to apply a model created using one set of images to images from other satellites or with different resolutions (Ghassemi et al., 2019; Rehman & Hussain, 2018)

Future methods can use Bayesian optimization or genetic algorithms to reduce the number of experiments required and not sacrifice the model's accuracy, according to (Jia et al., 2019; Kapoor et al., 2017).

.

CONCLUSION AND FUTURE WORK

A comprehensive review of academic literature on CNNs and satellite image segmentation reveals that many researchers are actively exploring different model architectures and optimization techniques to boost performance. In recent years, the critical role of hyperparameter tuning has become increasingly evident, especially in domains like medical image classification, remote sensing, and predictive modeling (Kimura et al., 2020; Abarja et al., 2020). Studies across various fields have evaluated tuning strategies such as Bayesian optimization, random search, genetic algorithms, and grid search, each differing in search efficiency and tuning accuracy (Krishnakumari et al., 2020; Lee et al., 2018).

This research contributes to the ongoing conversation by focusing on grid search optimization as a practical and user-friendly method for improving the accuracy of CNNs in satellite image processing tasks. Our experiments and analysis demonstrate that grid search can effectively enhance model performance in geospatial applications, making it a valuable tool for researchers and practitioners alike.

REFERENCES

[1] Achlioptas, P., Diamanti, O., Mitliagkas, I., & Guibas, L. (2017). Representation Learning and Adversarial Generation of 3D Point Clouds. 35th International Conference on Machine Learning, ICML 2018, 1, 67–85. Retrieved from https://arxiv.org/abs/1707.02392v1

[2] Ando, H., Niitsu, Y., Hirasawa, M., Teduka, H., & Yajima, M. (2016). Improvements of classification accuracy of film defects by using GPU-accelerated image processing and machine learning frameworks. In Proceedings - NICOGRAPH International 2016, NicoInt 2016 (pp. 83–87). Institute of Electrical and Electronics Engineers Inc. https://doi.org/10.1109/NicoInt.2016.15

[3] Assendorp, J. P., & Deep. (2017). Deep learning for anomaly detection in multivariate time series data. The Ninth International Conferences on Pervasive Patterns and Applications Defect 2017, 13(1), 1–12. Retrieved from https://www.metaljournal.com.ua/assets/Journal/english-edition/MMI_2015_7/045

[4] Chen, L. C., Papandreou, G., Kokkinos, I., Murphy, K., & Yuille, A. L. (2018). DeepLab: Semantic Image Segmentation with Deep Convolutional Nets, Atrous Convolution, and Fully Connected CRFs. IEEE Transactions on Pattern Analysis and Machine Intelligence, 40(4), 834–848. https://doi.org/10.1109/TPAMI.2017.2699184

[5] Christiansen, P., Nielsen, L. N., Steen, K. A., Jørgensen, R. N., & Karstoft, H. (2016). DeepAnomaly: Combining background subtraction and deep learning for detecting obstacles and anomalies in an agricultural field. Sensors (Switzerland),16(11). https://doi.org/10.3390/s16111904

[6] Ge, R., Zhu, Y., Xiao, Y., & Chen, Z. (2017). The subway pantograph detection using modified faster R-CNN. In Communications in Comput Information Science (Vol. 685, pp. 197–204). Springer Verlag. https://doi.org/10.1007/978-981-10-4211-9_20

[7] Han, Z., Wei, B., Mercado, A., Leung, S., & Li, S. (2018). Spine-GAN: Semantic segmentation of multiple spinal structures. Medical Image Analysis, 50, 23–35. https://doi.org/10.1016/j.media.2018.08.005

[8] Jabez, J., & Muthukumar, B. (2015). Detection Approach. Procedia - Procedia Computer Science, 48(Iccc), 338–346. Retrievedfrom http://dx.doi.org/10.1016/j.procs.2015.04.11

[9] Kaushik, P., & Jain, M. (2018). Design of low power CMOS low pass filter for biomedical application. International Journal of Electrical Engineering & Technology (IJEET), 9(5).

[10] Kaushik, P., Jain, M., & Jain, A. (2018). A pixel-based digital medical images protection using genetic algorithm. International Journal of Electronics and Communication Engineering, 31-37. http://www.irphouse.com/ijece18/ijecev11n1_05.pdf

[11] Kaushik, P., Jain, M., & Shah, A. (2018). A Low Power Low Voltage CMOS Based Operational Transconductance Amplifier for Biomedical Application.

https://ijsetr.com/uploads/136245IJSETR17012-283.pdf

[12] Kaushik, P., & Jain, M. A Low Power SRAM Cell for High Speed Applications Using 90nm Technology. Csjournals.Com,10. https://www.csjournals.com/IJEE/PDF10-2/66.%20Puneet.pdf

[13] Kaushik, P., & Jain, M. (2018). Design of low power CMOS low pass filter for biomedical application. International Journal of Electrical Engineering & Technology (IJEET), 9(5).

[14] Kaushik, P., Jain, M., & Jain, A. (2018). A pixel-based digital medical images protection using genetic algorithm. International Journal of Electronics an Communication Engineering, 31-37. http://www.irphouse.com/ijece18/ijecev11n1_05.pdf

[15] Kaushik, P., Jain, M., & Shah, A. (2018). A Low Power Low Voltage CMOS Based Operational Transconductance Amplifier for Biomedical Application. https://ijsetr.com/uploads/136245IJSETR17012-283.pdf

[16] Kaushik, P., & Jain, M. A Low Power SRAM Cell for High Speed Applications Using 90nm Technology. Csjournals. Com, 10. https://www.csjournals.com/IJEE/PDF10-2/66.%20Puneet.pdf

[17] Kermany, D. S., Goldbaum, M., Cai, W., Valentim, C. C. S., Liang, H., Baxter, S. L., … Zhang, K. (2018). Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning. Cell, 172(5), 1122-1131.e9. https://doi.org/10.1016/j.cell.2018.02.010

[18] Kim, J. Y., Bu, S. J., & Cho, S. B. (2017). Malware detection using deep transferred generative adversarial networks. In Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics) (Vol. 10634 LNCS, pp. 556–564). Springer Verlag. https://doi.org/10.1007/978-3-319-70087-8_58

[19] Kim, J. Y., Bu, S. J., & Cho, S. B. (2018). Zero-day malware detection using transferred generative adversarial networks based on deep autoencoders. Information Sciences, 460–461, 83–102. https://doi.org/10.1016/j.ins.2018.04.092

[20] Kos, J., Fischer, I., & Song, D. (2018). Adversarial examples for generative models. In Proceedings - 2018 IEEE Symposium on Security and Privacy Workshops, SPW 2018 (pp. 36–42). Institute of Electrical and Electronics Engineers Inc. https://doi.org/10.1109/SPW.2018.00014

[21] Larsen, A. B. L., Sønderby, S. K., Larochelle, H., & Winther, O. (2016). Autoencoding beyond pixels using a learned similarity metric. In 33rd International Conference on Machine Learning, ICML 2016 (Vol. 4, pp. 2341–2349). International Machine Learning Society (IMLS).

[22] Larsen, A. B. L., Sønderby, S. K., Larochelle, H., & Winther, O. (2016). Vae/Gan. Icml, 4, 2341–2349.

[23] Li, W., Wu, G., & Du, Q. (2017). Transferred Deep Learning for Anomaly Detection in Hyperspectral Imagery. IEEE Geoscience and Remote Sensing Letters, 14(5), 597–601. https://doi.org/10.1109/LGRS.2017.2657818

[24] Li, Y., Min, M. R., Shen, D., Carlson, D., & Carin, L. (2018). Video generation from text. In 32nd AAAI Conference on Artificial Intelligence, AAAI 2018 (pp. 7065–7072). AAAI press. https://doi.org/10.1609/aaai.v32i1.12233

[25] Madry, A., Makelov, A., Schmidt, L., Tsipras, D., & Vladu, A. (2018). Towards deep learning models resistant to adversarial attacks. In 6th International Conference on Learning Representations, ICLR 2018 - Conference Track Proceedings. International Conference on Learning Representations, ICLR.

[26] Makhzani, A., & Frey, B. (2017). PixelGAN autoencoders. In Advances in Neural Information Processing Systems (Vol. 2017-December, pp. 1976–1986). Neural information processing systems foundation.

[27] Nagahara, H., Umeda, K., & Yamashita, A. (2017). Thirteenth international conference on quality control by artificial vision 2017. In Proceedings of SPIE - The International Society

for Optical Engineering (Vol. 10338). https://doi.org/10.1117/12.2277475

[28] Puneet Kaushik, Mohit Jain , Gayatri Patidar, Paradayil Rhea Eapen, Chandra Prabha Sharma (2018). Smart Floor Cleaning Robot Using Android. International Journal of Electronics Engineering. https://www.csjournals.com/IJEE/PDF10-2/64.%20Puneet.pdf

[29] Puneet Kaushik, Mohit Jain , Gayatri Patidar, Paradayil Rhea Eapen, Chandra Prabha Sharma (2018). Smart Floor Cleaning Robot Using Android. International Journal of Electronics Engineering. https://www.csjournals.com/IJEE/PDF10-2/64.%20Puneet.pdf

[30]abokrou, M., Fayyaz, M., Fathy, M., & Klette, R. (2017). Deep-Cascade: Cascading 3D Deep Neural Networks for Fast Anomaly Detection and Localization in Crowded Scenes. IEEE Transactions on Image Processing, 26(4), 1992–2004. https://doi.org/10.1109/TIP.2017.2670780

[31] Sørensen, R. A., Rasmussen, J., Nielsen, J., & Jørgensen, R. N. (2017). Thistle detection using convolutional neural networks: EFITA 2017 Presentation. EFITA WCCA Congress. 2.-6. June 2017, 16(July), 1–15.Retrievedfrom https://www.mdpi.com/165332

[32] Srivastava, A., Valkov, L., Russell, C., Gutmann, M. U., & Sutton, C. (2017). VEEGAN: Reducing mode collapse in GANs using implicit variational learning. In Advances in Neural Information Processing Systems (Vol. 2017-December, pp. 3309–3319). Neural information processing systems foundation.

[33] Stentoumis, C., Protopapadakis, E., Doulamis, A., & Doulamis, N. (2016). A holistic approach for inspection of civil infrastructures based on computer vision techniques. In International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives (Vol. 41, pp. 131–138). International Society for Photogrammetry and Remote Sensing. https://doi.org/10.5194/isprsarchives-XLI-B5-131-2016

[34] Sung, F., Yang, Y., Zhang, L., Xiang, T., Torr, P. H. S., & Hospedales, T. M. (2018). Learning to Compare: Relation Network for Few-Shot Learning. In Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition (pp. 1199–1208). IEEE Computer Society. https://doi.org/10.1109/CVPR.2018.00131

[35] T., J. (2018). Comparative Study of GAN and VAE. International Journal of Computer Applications, 182(22), 1–5. https://doi.org/10.5120/ijca2018918039

[36] Tawara, N., Kobayashi, T., Fujieda, M., Katagiri, K., Yazu, T., & Ogawa, T. (2018). Adversarial autoencoder for reducing nonlinear distortion. In 2018 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference, APSIPA ASC 2018 - Proceedings (pp. 1669–1673). Institute of Electrical and Electronics Engineers Inc. https://doi.org/10.23919/APSIPA.2018.8659540

[37] V.N., E., & U.R., I. (2016). Modeling approaches for time series forecasting and anomaly detection. Animal Molecular Breeding, 8–13.

[38] Wang, H., Qin, Z., & Wan, T. (2018). Text generation based on generative adversarial nets with latent variables. In Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics) (Vol. 10938 LNAI, pp. 92–103). Springer Verlag. https://doi.org/10.1007/978-3-319-93037-4_8

[39] Yamashita, R., Nishio, M., Do, R. K. G., & Togashi, K. (2018, August 1). Convolutional neural networks: an overview and application in radiology. Insights into Imaging. Springer Verlag. https://doi.org/10.1007/s13244-018-0639-9

[40] Zhao, Y., Deng, B., Huang, J., Lu, H., & Hua, X. S. (2017). Stylized adversarial autoencoder for image generation. In MM 2017 - Proceedings of the 2017 ACM Multimedia Conference (pp. 244–251). Association for Computing Machinery, Inc. https://doi.org/10.1145/3123266.3123450

[41] Zhao, Z., Li, B., Dong, R., & Zhao, P. (2018). A surface defect detection method based on positive samples. In Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics) (Vol. 11013 LNAI, pp. 473–481). Springer Verlag. https://doi.org/10.1007/978-3-319-97310-4_54

[42] Zheng, Y. J., Zhou, X. H., Sheng, W. G., Xue, Y., & Chen, S. Y. (2018). Generative adversarial network based telecom fraud detection at the receiving bank. Neural Networks, 102, 78–86. https://doi.org/10.1016/j.neunet.2018.02.015

[43] Zhou, Y., & Tuzel, O. (2018). VoxelNet: End-to-End Learning for Point Cloud Based 3D Object Detection. In Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition (pp. 4490–4499). IEEE Computer Society. https://doi.org/10.1109/CVPR.2018.00472

[44] Puneet Kaushik, Mohit Jain, Study and Analysis of Image Encryption Algorithm Based on Arnold Transformation. International Journal of Computer Engineering and Technology, 9(5), 2018, pp. 59-63. http://iaeme.com/Home/issue/IJCET?Volume=9&Issue=5