Journal of Science and Technology
ISSN: 2362-1443 (Print) 3059-9490 (Online)2024,
Vol. 4, No. 2 (Special Issue), 7-13
DOI : https://doi.org/10.3126/jost.v4i2.78696

Anomaly Detection in Water Distribution Assets using Spatial and Channel Attention based on DenseNet 201

Kripesh Lamichhane
Nepal College of Information Technology
Pokhara University, Nepal
kripesh.192503@ncit.edu.np

Ashim Khadka*
Nepal College of Information Technology
Pokhara University, Nepal
ashim.khadka@ncit.edu.np

* Corresponding author

Article History:
Received: 24 July 2024
Revised: 8 August 2024
Accepted: 17 December 2024

Keywords— .Anomaly Detection, Attention Mechanism, CNN, DenseNet, Image Classification.

Abstract— **In the sector of water distribution management, anomaly detection is very important for maintaining operational efficiency and reliability, especially in the region where there are scarce resources. Though traditional CNNs (Convolutional Neural Networks) are effective in various image classification tasks, they often struggle with recognizing complex patterns in real-world datasets due to their limited capacity to dynamically focus on relevant features. This thesis addresses these limitations by introducing an attention module on top of a CNN-based model to improve the performance of the models. Results indicated that the attention-based DenseNet201 achieved an average recall of 95.53% and an F2 Score of 0.9552 on a novel dataset of tap images and it also outperformed the traditional CNN models. The enhancement of CNN with attention mechanism also highlighted the efficiency and accuracy of attention mechanisms in enabling the model to focus on important regions. This helped the model to work better even on images with complex backgrounds. This approach increases the capabilities of CNN-based systems for anomaly detection. Also, it offers a better solution for the automated monitoring of water distribution assets. This eventually contributes to the reduction of water wastage and improving infrastructure maintenance.**

I. INTRODUCTION

Understanding images is a major part of machine learning, mainly for image classification. This complex process involves steps such as preparing the image data, dividing it into meaningful parts, extracting important features, and finding relationships within the data [1]. New image classification methods have made it faster to understand what's in an image and have led to it being used in many areas, including science,city planning, public safety, medical imaging, and more.

Water supply across different locations relies heavily on global water distribution systems and the case is the same in the context of Nepal. The Water Supply and Sanitation (WSS), whose main focus is on rural water supply, is making strategy for upkeeping water sources and distribution assets so that there remains a reliable water supply and no substantial water loss. Though they are continuously monitoring water sources and distribution system, they rely on traditional methods for monitoring infrastructure, which mainly depend on manual inspections. The problem with manual inspection is that it requires a lot of labour and time,especially in distant areas that have limited resources and budgets. The manual inspections performed by humans are also error-prone and inefficient [2]. In this study, taps are considered as a water distribution asset. This water distribution asset plays a critical role in managing water flow and distribution. When considering taps as a water distribution asset, missing taps and taps that are not functioning properly can be considered as anomalies and these anomalies can severely impact the effectiveness of water distribution systems. The robustness and reliability of water infrastructure depend upon the detection and classification of these anomalies [3].

Convolutional Neural Networks (CNNs) have shown great success in image classification tasks. Architectures like VGG16[4], ResNet [5], and DenseNet [6] have significantly advanced the field. However, CNNs face challenges in real world data scenarios, such as overfitting, limited spatial relationship capture, and insufficient focus on critical image areas[7][8]. These limitations can hinder their effectiveness in real world image classification tasks that require precise anomaly identification [9] [10].

Attention mechanisms have made CNN models even better. These mechanisms let CNNs pinpoint crucial aspects of images by considering both the spatial layout of the image and the different colour channels used. This approach allows CNNs to focus on relevant areas and improve their ability to spot anomalies and subtle patterns, especially in large and complex datasets [11]. Spatial attention mechanisms help the model focus on crucial parts of an image, allowing it to better distinguish important objects from the image that has lots of background noise. Channel attention mechanisms give the model the ability to evaluate the significance of different feature channels, resulting in more accurate featurerepresentation and improved classification [12].

Various research shows that using attention techniques with CNNs as their base model makes the model even better [13]. By enhancing with attention,CNNs like VGG16, ResNet, and DenseNet have gotten much better at classifying images in applications like weather image recognition [14]. The research also shows that the calculation metrics increase by 0.2 to 1.3 percentage. Compared to regular CNNs, these enhanced systems are more accurate and reliable.

The primary objective of this research is to enhance the performance of traditional CNN architectures by integrating attention mechanisms for improved anomaly detection in water distribution assets. This study aims to address the inefficiencies of traditional and subjective manual inspections by comparing conventional CNN models with CNN models enhanced with attention mechanisms.

II. RELATED WORK

Image classification tasks have been significantly improved due to the recent advancements in Convolutional Neural Networks (CNNs). Bhujel incorporated attention modules to improve model performance. Various attention modules' efficacy was compared in plant disease classification in terms of the performance and computational complexity of the models. When CNN was enhanced with an attention mechanism, results showed that it improved the interclass precision and recall, thus increasing the overall accuracy (>1.1%.) [11].

Wang et. al proposed an architectural style classification method that was based on CNN and channel-spatial attention, where they added a preprocessing operation before CNN feature extraction and then use a CNN feature extractor for deep feature extraction. They then added, a channel–spatial attention module to generate an attention map, which not only enhanced the texture feature representation of architectural images but also focused on the spatial features of different architectural elements [15]

Guo et al. found that though attention mechanisms are widely used for performance enhancement, these existing methods either ignore the importance of using channel attention and spatial attention mechanisms simultaneously or bring much additional model complexity. To achieve a balance between performance and model complexity, they proposed Hybrid Attention Module, which is a combination of channel and spatial modules and experimental results showed that HAM integrated networks achieved accuracy improvements and further reduced the negative impact of less training data on deeper networks performance than its counterparts [16]. Wang et al. added a feature channel attention block to DenseNet to highlight the pneumonia information in the feature map, so that more weights are given to the areas that have pneumonia. Their method was found effective while evaluating the Chest X-ray 2017 dataset [15].

Kumar et al. collected 12,000 images from over 200 pipelines to train and test the neural networks. They used deep convoluted neural network models to diagnose faults in sewer systems,obtaining high accuracy [17]. Cheng et al. inspected various components of water infrastructure using computer vision techniques, such as the detection of pipe joints and detection of defects and damages to determine defect type [18]. Hang et al. proposed a hyper-spectral image classification method using an attention–aided CNN model. They designed two different classes of attention modules and incorporated them into the original CNN to construct a spectral attention subnetwork and a spatial attention subnetwork. Their integrated model significantly outperformed the original CNN [19]. Roy et al. found that conventional image classifiers perform well with preprocessed data, there is a high chance that if the same classifier is used in real-life tasks, they would fail drastically. So, they proposed a model that uses autoencoders along with CNN construct for classifying noisy data [20]. Woo et al. added the Convolutional Block Attention Module (CBAM) to CNN architectures [12], which enhanced the model's performance in a variety of image classification tasks by helping it focus on key features. Similarly, Barua et. al showed notable increases in feature extraction and classification accuracy by applying attention mechanisms to DenseNet models [21].

There have been some promising outcomes observed in the field of medical picture classification and environmental monitoring through the use of attention enhanced CNNs. For instance, Cai et al. achieved a better accuracy and efficiency for landslide detection using DenseNet with attention mechanisms than they did with conventional approaches. These experiments demonstrate how attention mechanisms might improve CNN models' performance across a range of anomaly detection tasks [22]. Also, Studies conducted by Zhong et al. and Albelwi have shown how combining attention mechanisms with CNNs may greatly increase the accuracy of anomaly identification in applications like cancer picture classification and weatherimage recognition [23] [18].

III. METHODOLOGY

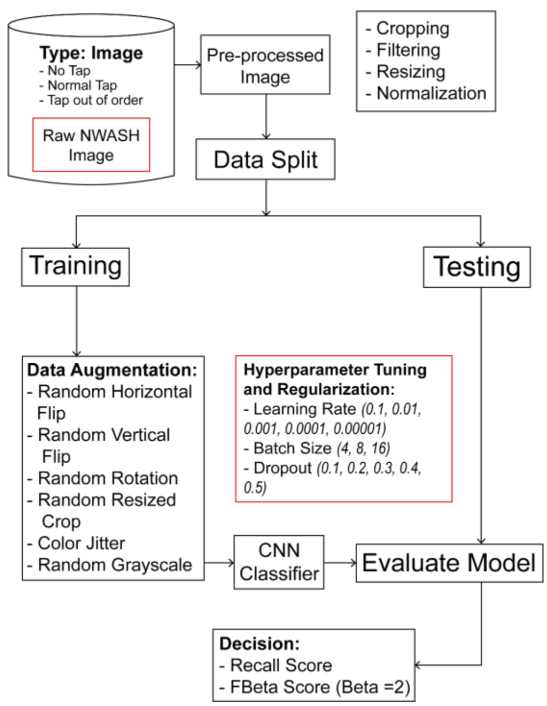

Fig. 1: Block diagram of the proposed methodology to detect anomalies in water distribution assets

A CNN model enhanced with an attention mechanism is developed for real-world image classification. The attention block is added to the base CNN model. By integrating the attention mechanism, meaningful features are being focused and irrelevant ones are ignored. This enhanced CNN model is supposed to result in improved feature extraction and representation. After fine-tuning the optimal model, the best calculation metrics are set to be achieved. Fig. 1 shows the block diagram of the proposed methodology to detect anomalies in water distribution assets.

A. Data Source

In this study, the dataset utilized is the Tap Image dataset provided by NWASH (National Water Supply and Sanitation Hygiene). The dataset consists of 12,155 images with dimensions of 224×224 pixels. The dataset comprises three classes: Normal Tap, No Tap, and Tap Out of Order. Taps out of order and missing taps which is No Tap as per our class are considered anomalous and Normal Tap is considered non anomalous. Table I shows the distribution of images into anomalous and non-anomalous.

TABLE I: Number of Images for Non-Anomalous and Anomalous Types

Non-Anomalous		Anomalous			
Type of Image	Count	Type of Image	Count	Type of Image	Count
Normal Tap	5325	No Tap	4100	Tap Out of Order	2730

Fig. 2 below shows the sample dataset of each class from the NWASH dataset. Fig. (2a) No Tap and (2c) Tap Out of Order are considered anomalous and Fig (2b) Normal Tap is considered non-anomalous.

(a) No Tap (b) Normal Tap (c) Tap Out of Order

Fig. 2: Sample Dataset

B. Data Preprocessing

First, the images provided by NWASH were cropped to reduce the background noise. Then the dataset was divided into three parts, training, testing, and validation. The reason for this split was that the split allows the model to be trained using part of the data called the training set and tested on different parts of the data called the testing set. This approach is to make sure the model performs well on unseen data too. To evaluate the model effectively, the data was split in the ratio 80:10 :10 where 80% of the data was allocated for the training dataset and 10% of the data was allocated for each testing and validation dataset. Fig. 3 shows the total no of images when split in the ratio 80:10:10.

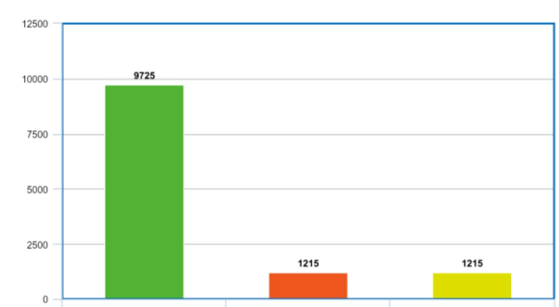

Fig. 3: Distribution of images in the NWASH dataset.

C. Image Transformations

1) Training Dataset: To enhance the robustness of the training data, the following augmentation and preprocessing transformations were applied to images resized to 224 × 224.

- RandomHorizontalFlip (p = 0.50) : Flips the image horizontally with a 50% probability.
- RandomVerticalFlip (p = 0.50) : Flips the image vertically with a 50% probability.
- RandomRotation (30): Rotates the image by a random angle up to 30 degrees.
- RandomResizedCrop (224, scale = (0.8,1.0)) : Randomly crops and resizes the image.
- ColorJitter (brightness=0.2, contrast=0.2, saturation=0.2, hue=0.2): Adjusts brightness, contrast, saturation, and hue.
- RandomGrayscale (p=0.1): Converts the image to grayscale with a 10% probability.
- Normalization is applied to each channel (Red, Green, Blue) of the image using the given formula:

$$\text{Normalized Value} = \frac{\text{Pixel Value} - 0.5}{0.5} \quad (1)$$

This normalization scales the pixel values to the range [−1,1], ensuring that the mean is 0 and the standard deviation is 1 for each channel. This standardization helps in improving the convergence and stability of the neural network during training. These transformations ensure that the training, testing,and validation data are sufficiently augmented and preprocessed for effective model training and evaluation.

2) Testing and Validation Dataset: For the testing and validation data, only preprocessing transformations, i.e.,normalization, was applied. This normalization scales the pixel values to the range [−1,1], ensuring that the mean is 0 and the standard deviation is 1 for each channel. This standardization helps improve the neural network's convergence and stability during training. The normalization can be calculated as eq. 1. These transformations ensure that the training, testing, and validation data are sufficiently augmented and preprocessed for effective model training and evaluation.

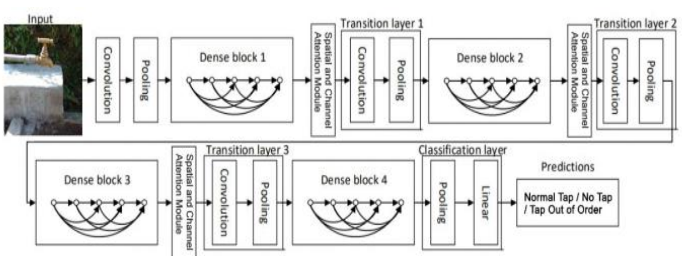

Fig. 4: DenseNet201 Architecture with Channel and Spatial Attention [24].

D. DenseNet201 combining Channel and Spatial Attention

In this section, a model is introduced where attention mechanisms are integrated into a DenseNet architecture for classification tasks. Fig. 4 shows the architecture of DenseNet201 with Channel and Spatial Attention.

Input Layer: The architecture is fed an image of size 224× 224.

Dense Blocks: 4 dense blocks with 6, 12, 48, and 32 Architecture layers are present in the DenseNet model.

Transition Layers: These layers reduce spatial dimensions and the number of channels. 3 transition layers are present.

Attention Module: An attention module weights feature maps to focus on important features. 2 CA blocks are used after SA block to enhance the representational feature.

Pooling Layer: Reduces parameters and dimensionality of feature maps. An adaptive average pooling layer was used.

Fully Connected Layer (FC): Connects neurons from preceding layers.3 output neurons were fed.

Output Layer: Final decision provided by the output layer.

Activation Function: Relu activation functions were used in convolutional and bottleneck layers.

Loss Function: Cross-entropy loss used for model evaluation.

E. Evaluation Metrics

Accurately classifying anomalies is crucial for monitoring and managing water distribution assets since it has a big impact on the dependability and efficiency of water distribution. Recall is crucial for these crucial classes, even if more conventional evaluation criteria like accuracy and precision are also vital. In many cases, the datasets can be imbalanced,meaning that some classes are represented more in comparison to others. In these cases, standard evaluation metrics like accuracy and precision could not offer a complete picture of the model's performance. The Fβ score provides a balanced metric that takes into account both false positives and false negatives. It is a weighted harmonic mean of precision and recall. Because the parameter beta allows for the adjustment of the relative relevance of precision and recall, it is especially useful in situations where recall is more important for particular classes.Precision, Recall, and F2 score are calculated as:

$$\text{Precision} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Positives (FP)}} \quad (2)$$

$$\text{Recall} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Negatives (FN)}} \quad (3)$$

$$\text{F2 Score} = \frac{(1+\beta^2)\cdot(\text{Precision}\cdot\text{Recall})}{(\beta^2\cdot\text{Precision}) + \text{Recall}} \quad (4)$$

IV. RESULTS AND DISCUSSION

A. Model Selection

Various CNN architectures such as ResNet9, VGG16,DenseNet121, DenseNet161, DenseNet169, and DenseNet201 were evaluated as a part of the first experiment. The experiment was also performed on 60 epochs and a batch size of 16. Other configurations like using Adam as an optimizer,using its default 0.001 learning rate, and Cross Entropy Loss as loss functions were default. Table II compares their performance metrics in terms of Recall, Precision, and F2 Score.

TABLE II: Comparison of various CNN Architectures

CNN Architectures	Recall	Precision	F2 Score
VGG16	0.9093	0.9045	0.9083
ResNet9	0.8763	0.8788	0.8766
DenseNet121	0.9067	0.9065	0.9067
DenseNet161	0.9087	0.9059	0.9081
DenseNet169	0.9024	0.9027	0.9025
DenseNet201	0.9123	0.9137	0.9126

Among the evaluated models, DenseNet201 demonstrated superior performance, leveraging its dense block architecture for efficient feature reuse and improved image feature representation.

B. DenseNet201 with Attention Mechanism

1) Hyperparameter Tuning: The Spatial and Channel Attention-based DenseNet201 model underwent hyperparameter tuning. Focus was made particularly on learning rate and batch size adjustments. The regularization technique, dropout was used since dropout regularization is crucial for preventing overfitting by randomly dropping units(along with their connections) during training,forcing the network to learn more robust features. After running through experiments, the optimal performance was achieved with a learning rate of 0.0001 and a batch size of 8, indicating the importance of these hyperparameters in model training. Also,adding dropout rates in the optimal model did not enhance model performance. Overall, the combination of spatial and channel attention added to DenseNet201 produced the best F2 Score of 0.9552.

2) Loss Curve and Accuracy curve: Visualizations were performed to analyze the optimal experiment using the Spatial and Channel Attention-based DenseNet201 architecture. Fig. 5 shows the loss curve and accuracy curve of the proposed model over 60 epochs. As the model trains over multiple epochs, the train loss and validation loss should ideally decrease, and the training accuracy and validation accuracy should increase to indicate that the model is generalizing well with minor overfitting.

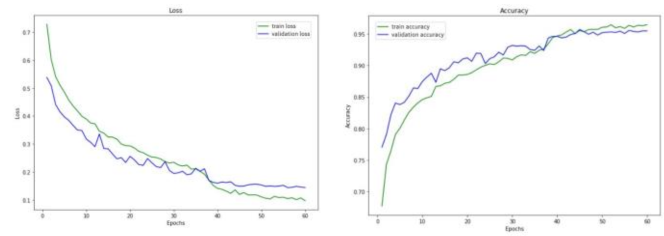

Fig. 5: Illustration of loss curve and accuracy curve of the proposed model over 60 epochs

Confusion Matrix and Precision-Recall Curve: Confusion matrices and precision-recall curves provide insights into the model's performance across classes as shown in fig. 6.

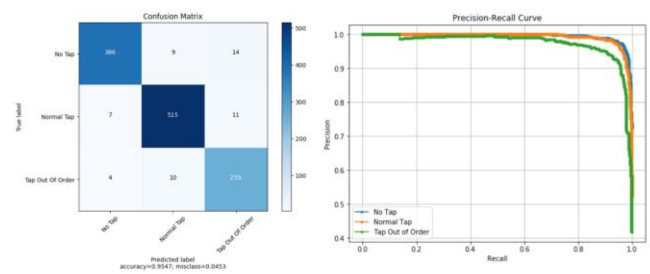

Fig. 6: Illustration of the confusion matrix and precision-recall curve of the test dataset on the proposed model

The confusion matrix resulted in 515 out of 533 images correctly identified. 7 are misclassified as No Tap and 11 as Tap Out of Order. For Tap Out of Order, 259 out of 273 images are accurately classified, although 4 are misclassified as No Tap and 10 are misclassified as Normal Tap. For No Tap, the model correctly identified 386 out of 409 images, with 14 misclassified as Tap Out of Order and 9 as Normal Tap. Also,the precision-recall curve showed that the model showed good performance, and maintained high precision for most of the recall range. The precision-recall curve shows that the proposed model provides high precision at low recall values and maintains the same high precision value as recall increases. The well-maintained precision across recall levels suggest that the model performs well in distinguishing between the different classes as supported by the confusion matrix. The confusion matrix also highlights that the model could improve, particularly in reducing the misclassifications.

C. K-Fold Cross Validation

K-Fold validation of the optimal model was performed using a subset of the dataset containing images of all the classes. To illustrate how well the model performed, train loss vs validation loss across 5-fold and train accuracy vs validation accuracy across each fold were compared. Table III presents the performance metrics across each fold, demonstrating the model's consistency and reliability.

TABLE III: Experiment on 5-folds cross validation on the proposed model

Fold	Recall	Precision	F2 Score
1	0.8735	0.8769	0.8742
2	0.8892	0.8892	0.8892
3	0.8583	0.8710	0.8608
4	0.8775	0.8801	0.8780
5	0.8711	0.8741	0.8717

Fig. 7 shows the loss curve and accuracy curve of 5-folds the cross -validation on the proposed model.

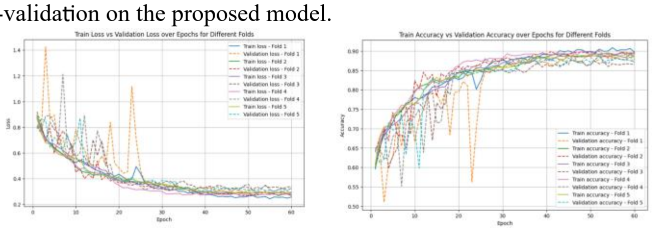

Fig. 7: Proposed model loss curve and accuracy curve on 5fold cross validation

D. Comparison with various attention mechanisms

Various attention mechanisms such as SEBlock, Channel Attention Block, Spatial Attention Block, and mixed Attention Block were applied to enhance the DenseNet201 model, the model that provided optimal results in the first experiment. The experiment was performed on 60 epochs a batch size of 8 and a learning rate of 0.0001. Other configurations like using Adam as an optimize, and Cross Entropy Loss as loss functions were default. Table IV compares their performance metrics in terms of Recall, Precision, and F2 score.

TABLE IV: Comparison between various attention mechanisms based DenseNet201

Attentton Mechanisms	Recall	Precision	F2 Score
SE Block	0.9424	0.9424	0.9424
Spatial	0.9358	0.9357	0.9358
Channel	0.9424	0.9426	0.9424
SpaSSal and Channel	0.9553	0.9548	0.9552

The combination of Spatial and Channel Attention mechanisms demonstrated the highest performance,enhancing classification accuracy and feature representation significantly, underscoring the importance of capturing both spatial and channel-wise information.

V.CONCLUSION

This research mainly focused on image classification tasks related to water distribution assets and water flow management. Experiments were first performed to explore the various Convolutional Neural Network architectures and find the best architecture for further experimenting. CNN architectures such as ResNet9, VGG16, DenseNet121 ,DenseNet161, DenseNet169, and DenseNet201. The results showed variations in calculation metrics such as recall,precision, and F2 score. From the experiment, the result showed that DenseNet 201 exhibited the highest recall of 0.9123 and precision of 0.9137 among the architectures tested. The DenseNet201 which was the optimal model in the first experiment, was then enhanced by adding an attention block. A combination of Spatial and Channel Attention blocks was added and it obtained the recall, and precision F2 score,all of which appeared to be 0.9382. To further enhance the performance of the model, regularization techniques,hyperparameter tuning, and fine -tuning approaches were used. Modifications in batch sizes, learning rates, and dropout rates were compared. The default parameters showed significant improvements in the F2 score which was 0.9552. These configurations included using the Adam optimizer with the cross-entropy loss function, a learning rate of 0.0001, and a batch size of 8. After that, the optimal model was compared with various attention mechanisms with the DenseNet 201. For future work, the contribution can be an addition to image classification by reducing the misclassification. There are other alternative approaches such as object detection and segmentation for performing anomaly detection in these kinds of real-world datasets. These techniques can offer complementary insights and may perform better in detecting anomalies that traditional classification methods might overlook.

REFERENCES

[1] T. Guo, J. Dong, H. Li, and Y. Gao, "Simple convolutional neural network on image classification," IEEE, 3 2017. [Online]. Available: https://doi.org/10.1109/icbda.2017.8078730

[2] G. Fu, Y. Jin, S. Sun, Z. Yuan, and D. Butler, "The role of deep learning in urban water management: A critical review," Water research, vol. 223, p. 118973, 9 2022. [Online]. Available: https://doi.org/10.1016/j.watres.2022.118973

[3] A. Hangan, C-.G. Chiru, D. Arsene, Z. Czako, D. F. Lisman,M. Mocanu, B. Pahontu, A. Predescu, and G. Sebestyen, "Advanced Techniques for Monitoring and Management of Urban Water Infrastructures - An Overview", Water, vol. 14, no. 14, p. 2174, 7 2022. [Online]. Available: https://doi.org/ 10.3390/w14142174

[4] K. Simonyan and A. Zisserman, "Very deep convolurronal networks for Large-Scale image recognition," arXiv (Cornell University), 1 2014. [Online]. Available: https:// arxiv.org /abs/ 1409.15

[5] K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 770-778, 6 2016. [Online]. Available: https:// doi.org/10.1109/ cvpr.2016.90

[6] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, "Densely Connected Convolutional Networks," Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 4700-4708., 7 2017. [Online]. Available: https://doi.org/10.1109/cvpr.2017.243

[7] Y. Guo, Y. Liu, A. Oerlemans, S. Lao, S. Wu, and M. S. Lew, "Deep learning for visual understanding: A review," Neurocomputing, vol. 187, pp. 27–48,4 2016. [Online]. Available: https://doi.org/10.1016/j.neucom.2015.09.116

[8] M. Zheng, J. Xu, Y. Shen, C. Tian, J. Li, L. Fei, M. Zong, and X. Liu, "Attention-based CNNs for image Classification: a survey,"Journal of physics. Conference series, vol. 2171, no. 1, p. 012068, 1 2022. [Online]. Available: https://doi.org/10.1088/1742-6596/2171/1/012068

[9] A. Nguyen, J. Yosinski, and J. Clune, "Deep neural networks are easily fooled: high confidence predictions for unrecognizable images," 2015.[Online]. Available: https://www.cv-foundation.org/ openaccess/contentcvpr 2015/ html/Nguyen Deep Neural Networks 2015 CVPR paper.html

[10] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," Nature, vol. 521, no. 7553, pp. 436–444, 2015. [Online]. Available: https://www.nature.com/articles/nature14539

[11] A. Bhujel, N.-E. Kim, E. Arulmozhi, J. K. Basak, and H.-T. Kim, "A lightweight Attention-Based convolutional neural networks for tomato leaf disease classification," Agriculture, vol. 12, no. 2, p. 228, 2 2022.[Online]. Available: https://www.mdpi.com/2077-0472/12/2/228

[12] S. Woo, J. Park, J. Y. Lee, and S.Kweon, "CBAM: Convolutional Block Attention Module," 2018. [Online]. Available: https://openaccess.thecvf.com/content ECCV 2018/html/Sanghyun Woo Convolutional Block Attention ECCV 2018 paper.html

[13] J. Hu, L. Shen, S. Albanie, G. Sun, and E. Wu, "Squeeze-and-Excitation networks," 9 2017. [Online]. Available: https://arxiv.org/abs/1709.01507

[14] S. A. Albelwi, "Deep Architecture based on DenseNet-121 Model for Weather Image Recognition," International journal of advanced computer science and applications/International journal of advanced computer science applications, vol. 13, no. 10, 1 2022. [Online]. Available: https://doi.org/10.14569/ijacsa.2022.0131065

[15] B. Wang, S. Zhang, J. Zhang, and Z. Cai,"Architectural style classification based on CNN and channel–spatial attention," Signal, image and video processing, vol. 17, no. 1, pp. 99–107, 4 2022. [Online]. Available: https://doi.org/10.1007/s11760-022-02208-0

[16] G. Li, Q. Fang, L. Zha, X. Gao, and N. Zheng, "HAM: Hybrid attention module in deep convolutional neural networks for image classification," Pattern recognition, vol. 129, p. 108785, 9 2022. [Online]. Available: https://www.sciencedirect.com/science/article/abs/pii/ S00313 203220 02667

[17] S. S. Kumar, M. Wang, D. M. Abraham, M. R. Jahanshahi, T. Iseley, and J. C. P. Cheng, "Deep Learning–Based Automated Detection of Sewer Defects in CCTV Videos," Journal of computing in civil engineering, vol. 34, no. 1, 1 2020. [Online]. Available: https://doi.org/10.1061/(asce)cp.1943-5487.0000866

[18] J. C. P. Cheng and M. Wang, "Automated detection of sewer pipe defects in closed-circuit television images using deep learning techniques,"Automation in construction, vol. 95, pp. 155–171, 11 2018. [Online]. Available: https://doi.org/10.1016/j.autcon.2018.08.006

[19] "Hyperspectral image classification with Attention-Aided CNNs," 3 2021. [Online]. Available: https://ieeexplore.ieee.org/document/9142417

[20] S. S. Roy, M. U. Ahmed, and M. A. H. Akhand, "NOISY IMAGE CLASSIFICATION USING HYBRID DEEP LEARNING METHODS," Journal of ICT, vol. 17 , 1 2018.[Online]. Available: https://doi.org/ 10.32890/jict2018.17.2.8253

[21] P. D. Barua, Dogan, G. Kavuran, T. Tuncer, R. Tan,and U. R. Acharya, "NFSDense201: microstructure image classification based on non-fixed size patch division with pre-trained DenseNet201 layers," Neural computing applications, vol. 35, no. 30, pp. 22253–22263 , 8 2023. [Online]. Available:https://doi.org/10.1007/s00521-023-08825-1

[22] H. Cai, T. Chen, R. Niu, and A. Plaza, "Landslide detection using densely connected convolutional networks