## A Systematic Reviews of Shared Weight Networks in Artificial Neural Network and Image Processing in Recent Research

### Surendra Kumar<sup>1</sup>, Dr. Jitender Rai<sup>2</sup>, Dr. K. P. Jayant<sup>3</sup>

<sup>1</sup> Research Scholar, Dept. of Computer Science and Engineering, Sunrise University, Alwar, Rajasthan

> <sup>2, 3</sup> Dept. of Computer Science and Engineering, Sunrise University, Alwar, Rajasthan

> > Email: Skgautam.Iitr@Gmail.Com

#### ABSTRACT

Improving system performance and efficiency depends much on the estimate of simulation time for the picture extraction process. The major influence of selecting the appropriate extraction technique on processing times and general system quality was shown by this work. Among the strategies investigated, the WLS approach especially seems to be the most effective. The results highlight the need of ongoing research and development in the area of image extraction and fusion, thereby opening the path for more sophisticated, effective, and flexible methods able to satisfy the rising needs of many uses. This review article is exploration of shared weight networks in artificial neural network and image processing through various reviews article published in recent research. Due to very new research area, we have mostly included the papers of recent time for exploration from recent research works for this paper.

#### Keywords: Shared Weight Networks, Artificial Neural Network, Image Processing.

#### I. INTRODUCTION

In the realm of artificial intelligence and computer vision, the ability to decipher and interpret visual data lies at the core of countless applications, from facial recognition to autonomous vehicles. Key to this capability is the process of feature Extraction, which involves identifying and isolating relevant patterns, edges, and structures within images. In recent years, the intersection of advanced artificial neural networks and image processing has revolutionized our ability to extract and harness these critical features effectively. One pivotal technique that has emerged as a cornerstone in this field is the utilization of shared weight networks within artificial neural networks [1]. This approach not only enhances the efficiency of feature Extraction but also unlocks the potential for remarkable advances in image recognition, object detection, and scene understanding. This research delves into the fascinating world of shared weight networks and their pivotal role in feature Extraction for image processing. We will explore the fundamental principles behind shared weight architectures, their application in convolutional neural networks (CNNs), and the remarkable strides they have enabled in creating translation-invariant and hierarchical representations of visual data [2]. Furthermore, we will examine real-world use cases, discuss the implications of weight sharing for computational efficiency, and touch upon the exciting frontiers of transfer learning and custom architecture design. Feature Extraction using shared weight networks in artificial neural networks is a technique commonly used in image processing and computer vision tasks [3]. This approach involves designing neural network architectures that share certain weights or parameters across multiple layers or units. This shared weight structure is particularly useful for tasks where translation invariance or learning of spatial hierarchies is important, such as image recognition and

object detection. Here's an overview of how shared weight networks are used in artificial neural networks for feature Extraction in image processing:

**Convolutional Neural Networks (CNNs):** CNNs are a class of neural networks that have become the standard for image processing tasks. They use shared weight networks in the form of convolutional layers. These layers consist of learnable filters or kernels that slide over the input image to extract local features. The weights in these filters are shared across different locations in the input image, allowing the network to capture spatial patterns and features [4].

**Weight Sharing in Convolutional Layers:** In convolutional layers, weight sharing means that the same set of filter weights is applied to different receptive fields across the input image. This enables the network to detect the same features (e.g., edges, textures) at different locations, making it translation-invariant. Weight sharing reduces the number of parameters in the network, making it computationally efficient.

**Feature Hierarchies:** CNNs often have multiple convolutional layers stacked on top of each other. These layers gradually learn hierarchical features, starting from simple ones like edges and gradually moving up to complex features like object parts and whole objects. Weight sharing allows each layer to build upon the features learned by the previous layer, creating a hierarchical representation of the input image [5].

#### **II. LITERATURE REVIEW**

Zhang et.al. (2021), Typically, conventional retrieval models based on deep learning are trained using the scene classification framework, employing cross-entropy loss. This approach primarily emphasizes the output probability associated with the input sample's label, disregarding the predictive information from other categories. Consequently, the accuracy of retrieval is vulnerable to the intraclass disparity among image samples. Conventional approaches often use convolution kernels of preset sizes, limiting their consideration to local areas and thereby neglecting global information to a significant extent. This paper presents a novel approach to address the aforementioned issues by introducing a triplet nonlocal neural network (T-NLNN) model that integrates deep metric learning with nonlocal operation. The T-NLNN, as suggested, adopts a network architecture consisting of three branches, whereby each branch shares weights. The authors conducted an evaluation of T-NLNN on three publicly available highresolution remote sensing datasets. The results of the experiments indicate that T-NLNN has a strong capacity to learn discriminative features and achieves superior performance compared to other algorithms currently in existence. Furthermore, the authors suggest the use of a dual-anchor triplet loss function as a means to enhance the usage of information contained within the input samples. The experimental findings demonstrate that the dual-anchor triplet loss function, as suggested, outperforms the classic triplet loss function across all datasets.

Li et.al. (2021), This research use a combination of convolutional neural networks (CNN) methodology with mid-infrared (MIR) spectra to identify sugar adulteration in honey. To enhance the comprehensibility of the model and capture the diversity across several classes, a CNN algorithm visualization is used for the purpose of honey adulteration identification. The co-activation of kernels is used to investigate nuanced aspects via the acquisition of distinct weights and biases. The signals that have been amplified or suppressed via the use of kernels have either positive or negative impacts on the model. In addition, the visible characteristics have been included to aid in the interpretation of spectroscopy. The findings of this study indicate that the Convolutional Neural Network (CNN) has remarkable potential in terms of accuracy when compared to the Least Squares Support Vector Machines (LS-SVM) and Partial Least Squares Discriminant Analysis (PLS-DA), particularly in the case of data received from the market.

Furthermore, this research provides empirical evidence that reinforces the theoretical and practical underpinnings of Convolutional Neural Networks (CNNs) in relation to feature selection, visualization, and model interpretation.

Sun, Y., & Yan, Z. (2021), The primary objective of target detection is to discern and ascertain the presence and spatial coordinates of targets within static pictures or sequences of video. This problem has significant importance within the domain of computer vision. The area of digital image processing has seen significant advancements in deep machine learning technologies, particularly in the convolutional neural network model. This model has shown a robust capability to extract picture features. Despite the fast development of target identification research with convolutional neural networks, practical implementations still encounter some challenges. For instance, the inclusion of several parameters in a detection model results in increased storage and computational expenses. Hence, this study aims to enhance and streamline certain algorithms via the use of early image detection techniques and convolutional neural network-based image detection algorithms. Following the completion of training and learning processes, the deployment of the Convolutional Neural Network (CNN) model will introduce the forward propagation mode. This mode facilitates the Extraction of image features, integration processing, and feature mapping inside the model. The use of backpropagation enables the convolutional neural network (CNN) model to possess the capacity for optimizing learning and implementing a compressed method. The purpose of this study is to examine and compare the Faster-RCNN algorithm with the YOLO algorithm. non-response to the issue of the insignificance of the candidate frame recovered non the Faster-RCNN method, we offer a target identification model that is based on the Significant Area Recommendation Network. The model calculates the weight of the feature map in order to amplify the saliency of the feature and minimize background interference. Empirical evidence demonstrates the viability of using a compressed neural network picture for image identification algorithms.

Liu et.al. (2020), The present study introduces a novel approach called Kernel-Blending Connection Approximation by Neural Network (KBNN) to address the task of picture categorization. A connection structure for kernel mapping, which is ensured by the function approximation theorem, has been developed to integrate feature Extraction and feature categorization using neural network learning. Initially, a feature extractor acquires knowledge of features from the unprocessed pictures. Subsequently, a kernel mapping connection that is created automatically is used to map the feature vectors into a feature space. Ultimately, a linear classifier is used as the output layer of the neural network in order to provide classification outcomes. Moreover, this study introduces a unique loss function that combines cross-entropy loss with hinge loss in order to enhance the neural network's capacity to generalize. The experimental findings obtained from three well recognized picture datasets demonstrate that the suggested methodology exhibits favorable classification accuracy and generalizability.

**Peng et.al. (2020),** The proliferation of mobile Internet and digital technologies has led to an increasing inclination among individuals to exchange images on social media platforms, resulting in a significant surge in online visual content. The retrieval of comparable pictures from a large-scale image database has consistently been a prominent concern within the domain of image retrieval. The effectiveness of image retrieval is significantly influenced by the use of image attributes. Convolutional Neural Networks (CNNs) include a greater number of hidden layers, resulting in a more intricate network structure and enhanced capacity for feature learning and expression as compared to conventional feature Extraction techniques. A suggested technique involves pooling low-level CNN feature maps to create local features, addressing the limitation of global CNN features in successfully describing local details during image

## Vol 3, Issue 10, October 2023www.ijesti.comE-ISSN: 2582-9734International Journal of Engineering, Science, Technology and Innovation (IJESTI)

retrieval tasks. The CNN model's high-level features prioritize semantic information, whereas the lowlevel features prioritize local details. Examining the progressive abstraction levels of the Convolutional Neural Network (CNN) model. This study introduces an algorithm for probabilistic semantic retrieval, suggests a technique for probabilistic semantic hash retrieval using CNN, and devises a novel supervised learning framework that enables simultaneous learning of semantic features and hash features for efficient picture retrieval. By using a convolutional neural network, the error rate in the given test set has been successfully decreased to 14.41%. A comparative analysis is conducted on the performance of classic SIFT-based retrieval techniques and alternative CNN-based image retrieval algorithms in three open picture libraries, including Oxford, Holidays, and ImageNet. The experimental findings demonstrate that the algorithm suggested in this study outperforms existing contrast algorithms in terms of both the overall effectiveness of retrieval and the time required for retrieval.

Tian, Y. (2020), The convolutional neural network (CNN) is a very efficient method that has gained significant popularity in the domain of image processing. Its effectiveness stems from its use of local receptive fields, weight sharing, pooling, and sparse connections, which all contribute to its impressive performance and successful outcomes. This research presents a novel convolutional neural network technique with the aim of enhancing the convergence speed and recognition accuracy. In this study, we propose the integration of a recurrent neural network (RNN) into a convolutional neural network (CNN) architecture. This integration allows for the simultaneous learning of deep features from images utilizing both the CNN and RNN components. Furthermore, in accordance with the concept of the skip convolution layer in ResNet, we have developed a novel residual module called ShortCut3-ResNet. Subsequently, a dual optimization model is formulated to achieve the combined optimization of the convolution and full connection processes. In conclusion, this study examines the impact of different parameters of the convolutional neural network on its performance by conducting simulation tests. Subsequently, the best network parameters for the convolutional neural network are determined. The experimental findings demonstrate that the convolutional neural network technique introduced in this study has the capability to acquire a wide range of image features, hence enhancing the accuracy of feature Extraction and image recognition proficiency of the convolutional neural network.

Huixian, J. (2020), The classification and identification of plants play a crucial role in facilitating individuals' comprehensive comprehension and conservation efforts pertaining to plant species. The foliage of plants serves as the primary extraction y organs for recognition. The use of artificial intelligence and machine vision technology has facilitated the advancement of plant leaf identification technology, which relies on image analysis. This technology has been crucial in enhancing our understanding of plant categorization and protection. Deep learning is a shortened term referring to the process of learning in deep neural networks, which are a specific kind of neural network architecture. The proposed approach involves the use of big data to automatically extract features, followed by the application of an artificial neural network that employs the back propagation method for the purpose of training and classifying plant leaf samples. The primary focus of this study is to extract characteristics from plant leaves and then identify plant species via the use of image analysis techniques. To begin with, plant leaf pictures undergo segmentation using a variety of approaches. Subsequently, a feature Extraction algorithm is used to extract both leaf form and texture data from the obtained leaf sample images. The comprehensive characteristic information of plant leaves is derived based on the comprehensive characteristic information. This study examines and evaluates the performance of 50 plant leaf datasets using three different classification algorithms: KNN-based neighborhood classification, Kohonen network based on self-organizing feature mapping technique, and SVM-based support vector machine. Simultaneously, a comparative analysis was conducted on the leaves of seven distinct plant species, revealing that ginkgo leaves exhibited a higher degree of ease in terms of identification. Significant progress has been made in achieving favorable identification outcomes for leaf photos captured against intricate backgrounds. The learning model is fed with image samples from the test set in order to calculate the reconstruction errors. The class label of the test set may be determined by recreating the deep learning model that exhibits the lowest mistake rate. The findings indicate that this particular approach exhibits the most efficient recognition time and the greatest percentage of accurate recognition.

#### **III. CONCLUSION**

The estimation of simulation time for the image extraction process is a vital aspect of enhancing system performance and efficiency. This study has demonstrated the significant impact of choosing the right extraction method on processing times and overall system quality. The WLS method, in particular, stands out as the most efficient among the methods examined. The findings underscore the importance of continuous research and development in the field of image extraction and fusion, paving the way for more advanced, efficient, and versatile techniques that can meet the growing demands of various applications. The integration of deep learning methods and optimization of existing algorithms will be crucial in achieving these goals, ultimately contributing to the advancement of technology and its applications in diverse fields.

#### REFERENCES

- 1. Li, W., Yang, C., Peng, Y., & Du, J. (2022). A pseudo-siamese deep convolutional neural network for spatiotemporal satellite image Extraction. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *15*, 1205-1220.
- 2. Dong, Y., Liu, Q., Du, B., & Zhang, L. (2022). Weighted feature Extraction of convolutional neural network and graph attention network for hyperspectral image classification. *IEEE Transactions on Image Processing*, *31*, 1559-1572.
- 3. Chen, S., Yu, J., & Wang, S. (2022). One-dimensional convolutional neural network-based active feature Extraction for fault detection and diagnosis of industrial processes and its understanding via visualization. *ISA transactions*, *122*, 424-443.
- 4. Ranjbarzadeh, R., Tataei Sarshar, N., Jafarzadeh Ghoushchi, S., Saleh Esfahani, M., Parhizkar, M., Pourasad, Y., ... & Bendechache, M. (2022). MRFE-CNN: Multi-route feature Extraction model for breast tumor segmentation in Mammograms using a convolutional neural network. *Annals of Operations Research*, 1-22.
- 5. Siar, M., & Teshnehlab, M. (2022). A combination of feature Extraction methods and deep learning for brain tumour classification. *IET Image Processing*, *16*(2), 416-441.
- 6. Anitha, K., & Srinivasan, S. (2022). Feature Extraction and Classification of Plant Leaf Diseases Using Deep Learning Techniques. *Computers, Materials & Continua*, 73(1).
- Zhang, C., Feng, Y., Hu, L., Tapete, D., Pan, L., Liang, Z., ... & Yue, P. (2022). A domain adaptation neural network for change detection with heterogeneous optical and SAR remote sensing images. *International Journal of Applied Earth Observation and Geoinformation*, 109, 102769.
- 8. Zhang, Z., & Wang, M. (2022). Convolutional neural network with convolutional block attention module for finger vein recognition. *arXiv preprint arXiv:2202.06673*.

# Vol 3, Issue 10, October 2023www.ijesti.comE-ISSN: 2582-9734International Journal of Engineering, Science, Technology and Innovation (IJESTI)

- 9. Tripathy, S., & Singh, R. (2022, January). Convolutional neural network: an overview and application in image classification. In *Proceedings of Third International Conference on Sustainable Computing: SUSCOM 2021* (pp. 145-153). Singapore: Springer Nature Singapore.
- Ravikumar, A., Sriraman, H., Saketh, P. M. S., Lokesh, S., & Karanam, A. (2022). Effect of neural network structure in accelerating performance and accuracy of a convolutional neural network with GPU/TPU for image analytics. *PeerJ Computer Science*, 8, e909.
- 11. Zhang, M., Cheng, Q., Luo, F., & Ye, L. (2021). A triplet nonlocal neural network with dualanchor triplet loss for high-resolution remote sensing image retrieval. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 14, 2711-2723.
- 12. Li, Q., Zeng, J., Lin, L., Zhang, J., Zhu, J., Yao, L., ... & Wu, Z. (2021). Mid-infrared spectra feature Extraction and visualization by convolutional neural network for sugar adulteration identification of honey and real-world application. *Lwt*, *140*, 110856.
- 13. Sun, Y., & Yan, Z. (2021). Image target detection algorithm compression and pruning based on neural network. *Computer Science and Information Systems*, *18*(2), 499-516.
- Liu, X., Zhang, Y., Bao, F., Shao, K., Sun, Z., & Zhang, C. (2020). Kernel-blending connection approximated by a neural network for image classification. *Computational Visual Media*, 6, 467-476.
- 15. Peng, X., Zhang, X., Li, Y., & Liu, B. (2020). Research on image feature Extraction and retrieval algorithms based on convolutional neural network. *Journal of Visual Communication and Image Representation*, 69, 102705.
- 16. Tian, Y. (2020). Artificial intelligence image recognition method based on convolutional neural network algorithm. *IEEE Access*, *8*, 125731-125744.
- 17. Huixian, J. (2020). The analysis of plants image recognition based on deep learning and artificial neural network. *IEEE Access*, *8*, 68828-68841.