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Robust Land Cover Change Detection using Optimized Convolutional Neural Network with SOM and PCNN classification

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ABSTRACT

Aim: To look at the correctness of Self Organising Map (SOM) with Pulse Coupled Network (PCNN) and Convolutional Neural Network (CNN) for ordering land cover data. **Materials and Methods:** This examination study utilized 10 samples with two gatherings of calculations showing up from g-power investigation with alpha blunder of 0.95, edge worth of 0.05, certainly level of 95%, Pre-test g-power of 80%. The multi unearthly photos from satellites for utilizing the order. This examination proposes a straightforward CNN structure with a thick component finder for picture arrangement. **Results:** SOM has achieved an accuracy of 97.37% and PCNN has achieved an accuracy of 95.25%. Among the two algorithms SOM performed better than PCNN with a 'p' value less than 0.05. **Conclusion:** The mean accuracy of SOM is significantly better than the mean accuracy of PCNN for detecting the land cover changes.

Keywords: Deep Learning, Innovative Land Cover Classification, Landscape Metrics, Image classification, Convolutional Neural Network, SOM, PCNN.

INTRODUCTION

Land cover grouping manages identifying the actual cover on the world's surface using image classification techniques. It significantly centers around Presence of Vegetation, Edaphic Condition and Artificiality of cover (Seydi, Hasanlou, and Amani 2020). Satellites far away detecting bundles have delivered a document of photos of the earth that are transforming into an expanding number of valuable supplies of records to get some answers concerning Landscape Metrics and land use change. Innovative Land cover classification order is significant for natural checking and distant observing (Chan, Cheung-Wai, and Chan, n.d.). The use of land cover order is to keep up with land cover records by managerial divisions in the regions (Bouchaffra and Ykhlef 2021). This exploration study discovers its application in rustic regions where there is a need to recognize the area of land that can be utilized for development (Sensing et al. 2017) (Twisa and Buchroithner 2019)

There are 212 exploration articles distributed in Google Scholar, over the most recent five year. Most of these have used deep learning algorithms with image classification for detecting Landscape Metrics. A considerable lot of these examinations have zeroed in on scene measurements. The exploration article that reviews the utilization of Convolutional Neural Network for Robust land cover grouping has 23 references and this investigation has accomplished 91.6% exactness (Jing, Gong, and Guan 2020). A fascinating methodology of partitioning the arrangement task into genuinely significant subsets of trademark target properties and significant imaging boundaries brought about a precision of 89.2% (Twisa and Buchroithner 2019). A relative investigation of CNN, Random Forest (RF) and Support Vector Machines for land cover order utilized phenological cycles in the ghostly bend pictures. They utilized the phantom pictures caught for a district in New Hampshire, USA, and showed that Convolutional Neural Network performed better compared to RF and SVM with an accuracy of 89.7% (Jude Hemanth 2019). A repetitive adaptation of FuseNet with full fix naming methodology utilizing Worldview-03 Quezon City dataset had brought about an exactness of 90.35% (He and Weng 2018).Previously our team has a rich experience in working on various research projects across multiple disciplines(Ezhilarasan et al. 2021; Balachandar et al. 2020; Muthukrishnan et al. 2020; Kavarthapu and Gurumoorthy 2021; Sarode et al. 2021; Hannah R et al. 2021; Sekar, Nallaswamy, and Lakshmanan 2020; Appavu et al. 2021; Menon et al. 2020; Gopalakrishnan et al. 2020; Arun Prakash et al. 2020)

The current investigation utilized SOM for grouping the phantom pictures into covered land and uncovered land and accomplished an exactness of 95.8% (Zhang et al. 2018). The proposed framework utilizes PCNN with a thick element locator for creative land cover arrangement. The point of this investigation is to contrast the exactness of Auto Encoder and Self Organising Map (SOM) and Pulse Coupled Neural Network (PCNN) for grouping Innovative land cover classification data.

MATERIALS AND METHODS

The examination study was done in the Data Analytics lab of Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences. In this exploration concentrate there are two gatherings to be specific: SOM and PCNN. The G Power examination was utilized to decide the example size as 670. Force examination was completed with the mean worth of 97 and standard deviation of 0.6 for both the gatherings. Because of the consistency of the outcomes i.e with no difference in precision, it was chosen to restrict the quantity of tests to 10.

The informational index was gathered from the Kaggle site that was kept refreshed on 21-Jun-2020 (Canty 2019). The dataset involving the woods, land, water, trees and metropolitan pictures was utilized. All together 880 pictures were found in the dataset. The quantity of pictures was shifted in each example. For both the examples, the example planning technique continued as before.

Algorithm for Self Organising Map (SOM)

At first CNN was arranged with five secret layers and three hubs in every one of the layers. A reasonable enhancer and the expense capacities were picked. The quantity of images to run and the quantity of groups in every image were set up. In every page, the predefined number of images were run and in every one of the groups, the highlights were removed from the pictures and the expense work was figured out. On the off chance that the expense work is over a limit esteem the enhancer streamlines it in the bunch. The over two stages were rehashed for the predetermined number of images.. Toward the finish of the execution of the predetermined number of images, the calculation yielded a model. This model was utilized for image classification and to foresee the class names for the pictures in the test set and likewise the exactness was determined.

Algorithm for Pulse Coupled Neural Network

As the highlights removed from the picture sets are directly related, straight bit work was arranged as the initial step. An inventive arrangement was finished by characterizing the expense work and the underlying worth of part coefficient (gamma). The punishment boundary of the mistake term was instated as 1. Utilizing the separated highlights, the worth of alpha was determined and was then enhanced. This progression was rehashed till an improved worth of alpha was shown up at. Utilizing the enhanced worth of alpha, the pictures in the preparation set were learnt and this brought about a model. This model was utilized for image classification to anticipate the land cover for the pictures in the testing set. In light of the forecasts, precision of PCNN was determined.

To complete this examination, the testing arrangement for both the gatherings was finished utilizing an Intel i3 Processor with a hard circle of 50 GB and a RAM of 4 GB. Matlab was utilized as the information science stage to carry out the calculations, SPSS v21 was utilized for measurable investigation. However every one of these products can run on any of the working frameworks, in this investigation, Windows 10 was utilized as a working framework. For testing the gatherings, the dataset was parted into a preparation set and a testing set at 85% and 15% separately. Both SOM and PCNN calculations were prepared utilizing the preparation set and it was tried utilizing the test set.

Statistical Analysis

The statistical analysis was carried out using SPSS v21 (Pallant 2020). The date, location and the land related information are the independent variables and remain constant even after changing other parameters, whereas image pixels, image color and image size are dependent variables depending on the inputs and vary for every change in the input.Statistical analysis was done using an independent 2-tailed sample t-test.

RESULTS

For ten trials, the testing yield for example the correctnesses of SOM and PCNN were gathered as information yield. This was rehashed for ten unique rates of preparing and testing information. The information yield gathered from the testing of two gatherings SOM and PCNN is portrayed in Table 1. The exactnesses of SOM and PCNN calculations for various sizes of Image classification set was plotted in a line diagram as displayed in Fig. 1. In this chart, precision esteems are brought to the y-pivot, and the quantity of Images were brought. The exactnesses of SOM and PCNN seen in every one of the preliminaries is plotted in Fig. 2. Table 2 portrays the factual investigation utilizing SPSS with the yields got from the testing. The investigation of results portrayed in Table 3 uncovers that the examination of correctnesses of PCNN and SOM has a measurable meaning of 0.001. For Landscape Metrics characterization, the mean exactness of PCNN is 97.37% and is fundamentally more than the mean precision of SOM (95.25%) when an example size of 10 was utilized.

DISCUSSION

In this investigation, it is observed that PCNN has better accuracy than Convolutional Neural Network with a p-worth of under 0.05 in the independent 2-tailed sample t-test. Inside the constraints of this examination, the trial results uncover that the current exploration arranges Landscape Metrics with a peak accuracy of 95.9% and the proposed framework accomplished 98.4% peak accuracy.

One of the past investigations utilized SOM with Adam analyzer for Robust Innovative land cover classification arrangement and recorded a precision of 92.4% (Ban 2016). This is in agreement with the discoveries from our investigation that the precision of SOM is not exactly the exactness of PCNN. EO1 Hyperion sensor pictures from Phulambri, Aurangabad, MH, India were utilized by an investigation to characterize the land cover with SOM and accomplished an exactness of 74.9% (Prasad and Chanussot 2020). A fix based PCNN was utilized in one of the past investigations and they tracked down that the pictures from Florida Everglades environment were grouped with 97.21% of exactness (IEEE Staff 2018). Another examination ordered a period series of satellite pictures utilizing PCNN by inferring multitemporal spatial information and accomplished 96.9% of precision (Zin and Lin 2018). There is an examination that pre-owned SOM with SAT4 and SAT6 airborne pictures and accomplished an exactness of 99.01% for SAT4 pictures and 99.44% for SAT6 pictures. This is negating the discoveries from our examination. The justification for the inconsistency is that they utilized a pooling layer for dimensional decrease and they utilized an imageset with 5,00,000 pictures. When contrasted with the quantity of pictures utilized in our examination, their imageset size is extremely high. Notwithstanding that the presentation of a pooling layer utilized more memory.

In this investigation, the quantity of covered up layers of PCNN and furthermore the quantity of hubs in every one of the secret layers was subjectively fixed. This is the first limitation and the second limitation is that an imageset with a predetermined number of 220 pictures was utilized. In future this examination can be reached by showing up at the quantity of covered up layers and the quantity of hubs in every one of the secret layers utilizing an enhancement procedure. In future this investigation can be rehashed with a huge imageset to discover the improvement in precision.

CONCLUSION

Accurate detection of land cover is performed to classify the satellite images of the world's surface. From this study, it is concluded that for identifying the Innovative Land cover classification, the mean accuracy of SOM is significantly more than the mean accuracy of PCNN with a 'p' worth of 0.002 when a sample size of 10 was utilized.

DECLARATIONS

Conflict of Interests

No conflict of interests in this manuscript

Authors Contributions

Author SS was involved in data collection, data analysis, manuscript writing. Author PR was involved in conceptualization, data validation, and critical review of manuscript.

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TABLES AND FIGURES

Table 1. Accuracies of SOM and PCNN across the Trails (Sample size = 10, Dataset size = 670, Peak Accuracy of SOM=95.9% and Peak Accuracy of PCNN = 98.4%)

Trail No	Data Size	% of Training data	% of Testing data	Accuracy of SOM	Accuracy of PCNN
1	2831	95	5	94.6	96.6
2	2831	93	8	94.8	96.8
3	2831	91	9	94.9	96.7
4	2831	89	11	95.0	96.9
5	2831	87	13	95.2	97.2
6	2831	85	15	95.3	97.4
7	2831	83	17	95.4	97.6
8	2831	81	19	95.6	97.9
9	2831	78	21	95.8	98.2
10	2831	75	25	95.9	98.4

Table 2. Statistical Analysis of the Results (Sample Size = 10, Mean Accuracy of SOM = 95.25 and the Mean Accuracy of PCNN = 97.37)

Algorithm	N	Mean	Std. Deviation	Std. Error Mean
SOM	10	95.25	.433	.137
PCNN	10	97.37	.641	.203

Table 3. Independent sample test analysis using 2-tailed test (Calculated p-value = 0.001, alpha = 0.05 and the Confidence Interval = [-17.154, -9.176])

	F	**sig.**	**t**	**df**	**sig.(2-tailed)**	**Mean difference**	**Std.error difference**	**95%confidence lower**	**95%confidence upper**
Equal variances assumed	.310	0.564	-10.071	18	.001	-11.600	1.152	-14.020	-9.180
Equal variances not assumed	NA	NA	-10.071	17.582	.001	-11.600	1.152	-17.024	-9.176

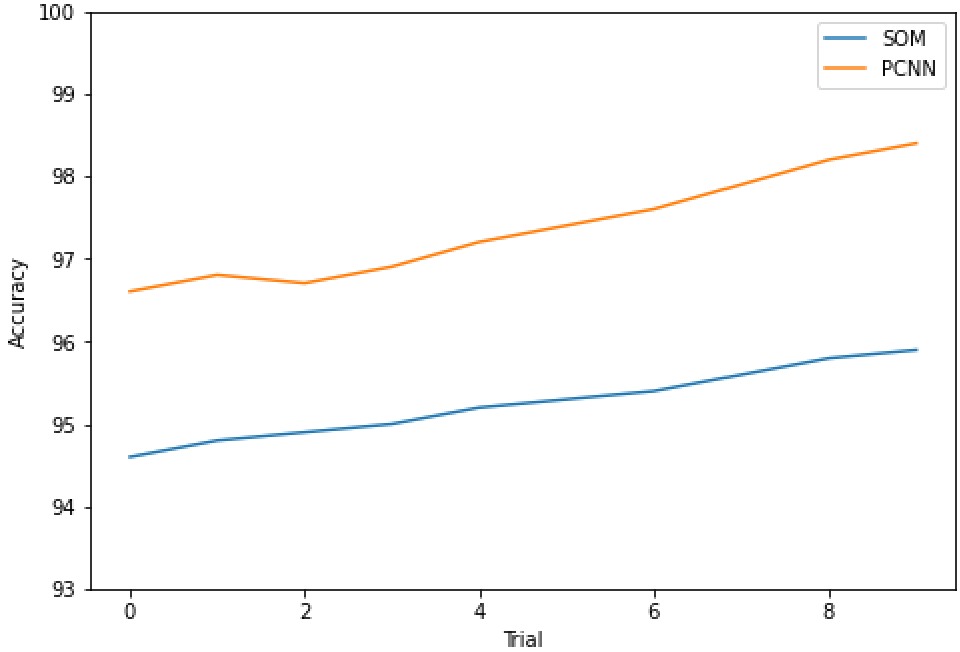

Fig. 1. Comparison of Accuracies of SOM and PCNN across the trials (Sample Size = 10, X-Axis: Trial No. and Y-Axis: Accuracy. In all the trials the accuracy of PCNN is more than the accuracy of SOM)

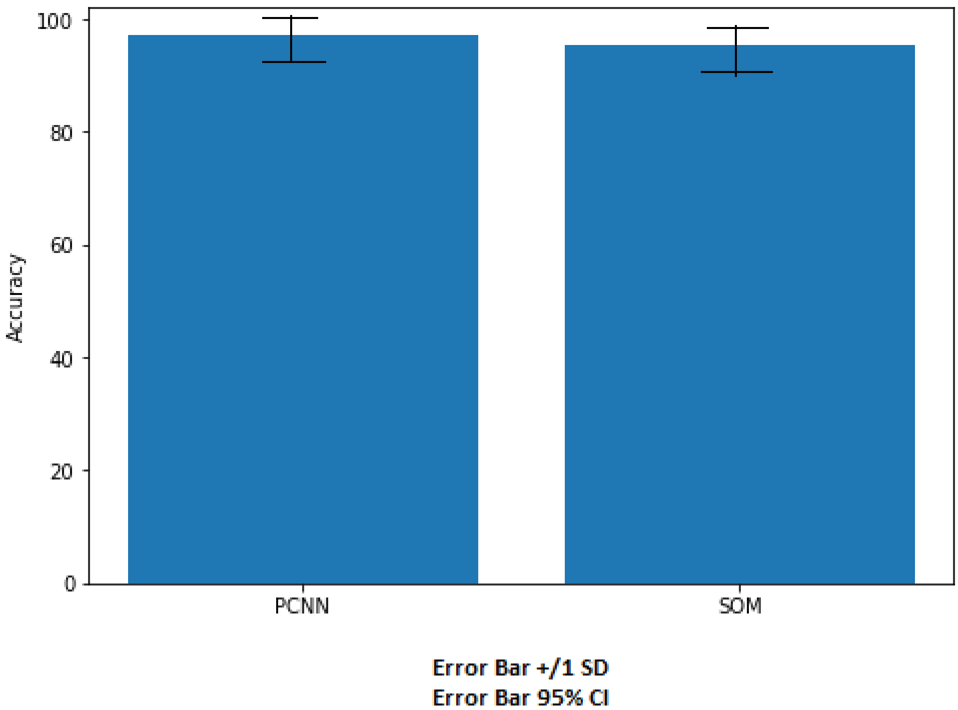

Fig. 2. Comparison of MeanAccuracies of SOM and P-CNN (SOM Accuracy: 95.25%, PCNN Accuracy: 97.37%, Confidence Interval = 95%, Error Bar = +/-1 SD, Standard Error Mean for CNN = 0.875, Standard Error Mean for PCNN= 0.749, hence Standard Error Mean is less for PCNN)