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Developing An Innovative Image Processing Model For Computer Networks through Optimized K-Nearest Neighbour Algorithm

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Abstract: Image processing is the process of enhancing or extracting information from images. It includes a wide range of methods, including segmentation and pattern recognition. In the context of computer networks, image processing is critical for enhancing data transfer and communication efficiency. The integration of image processing with computer networks improves the overall efficiency of visual information collaboration, which leads to innovations in various domains. In this research, we developed a novel machine learning-based image data processing model for computer networks named Red Deer optimized Adaptive K-Nearest Neighbour (RD-AKNN). We gathered a dataset that includes various types of image data to train our proposed approach for image processing. The data cleaning process is performed to reduce the redundancy, Global Contrast Normalization (GCN) algorithm is utilized to pre-process the gathered raw data. Red Deer Optimization (RDO) is employed to enhance the crucial characteristics of the suggested AKNN architecture for developing an innovative mage data processing model in computer networks. We implemented our proposed methodology in Python software. The finding analysis phase is performed with various metrics such as recall (97.5%), accuracy (97.2%), F1-score (98.3%) and precision (98.1%) to evaluate the proposed algorithm with other conventional methodologies. The experimental results demonstrate that the proposed RD-AKNN approach performed better than other conventional approaches for enhanced image data processing in computer networks.

Keywords: *Computer Networks, Image Processing, Machine Learning and Image Data, Red Deer Optimized Adaptive K-Nearest Neighbour (RD-AKNN)*

1. Introduction

In the modern constantly shifting technological world, integrating innovative approaches is critical for meeting the expanding needs of modern computer networks. Improving image processing efficiency is a crucial issue for computer networks that necessitates innovative solutions [1]. The increasing need for multimedia, high-resolution content and the widespread use of visual data on digital platforms has emphasized the importance of effective image-processing techniques [2].

Computer networks facilitate quick data sharing and global communication. Multimedia data must be transferred through this network [3]. Conventional image processing techniques are intense to keep up with the increasing number and complication of images in terms of speed, accuracy and resource usage. Algorithms employed in computer networks for image processing require considerable innovation [4].

The enhanced image-processing techniques intend to advance the field by surpassing the basic constraints of prior technologies. The model leverages complicated algorithms, neural networks and advanced machine-learning techniques to enhance the performance of image-processing tasks in various network circumstances [5]. The model makes use of algorithms to improve performance and respond quickly to the steadily changing information offered by networks.

Technologies such as virtual reality, live streaming and video conferencing depend on real-time image processing for their functionality [6]. The design of the system depends on sarcastic latency and maximizing data processing speed to enable effective handling of image data without condensing quality. This is essential in circumstances when quick decisions based on visual data are essential, such as with autonomous vehicles or monitoring systems [7].

It promotes resource adaptability and functions well in

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resource-constrained environments that are familiar with Internet of Things (IoT) applications. The strategy uses computer resources to develop system performance and reduce energy usage while processing images on computers [8].

Image data is processed in computer networks employing the Red Deer optimized Adaptive K-Nearest Neighbour (RD-AKNN) method.

The article is divided into the following sections: Related works, methodology, results and conclusion.

2. Related Works

Study [9] designed a diagnostic method using a deep-learning system to classify ocular disorders into four categories by automatically detecting drusen, diabetic macular edema, normal images and choroidal neovascularization in “optical coherence tomography (OCT) images of the human eye”. The dataset chosen for their study had constraints as it included scans from one demographic location and lacked variation in terms of eye shape across various races.

Study [10] provided an accessible description of deep learning (DL) in the processing of medical images, establishing fundamental concepts and progressing to practical implementations. Security and comprehension of networks remained as major issues. Paper [11] provided an in-depth examination of algorithm unrolling, beginning with the Learned Iterative Shrinkage and Thresholding Algorithm (LISTA) as a fundamental instance. They demonstrated practical uses of unrolling in different actual signal and image processing circumstances.

Study [12] presented an in-depth assessment of image quality assessment (IQA) models to evaluate their effectiveness as optimization goals for the processing of images. They carried out an extensive examination of perceptual optimization for four basic visual tasks, using guidance from eleven full-reference IQA frameworks. Their considerable difficulty in processing and lack of comprehension could restrict their usage.

Research [13] utilized a DL approach that employs methods for image processing to classify solder paste issues on “printed circuit boards (PCBs)” and identify their locations to avoid incorrect manufacturing due to flaws in the solder paste. Research [14] provided a powerful and widely used structure for Network Intrusion Detection Systems (NIDS) that combines the processing of images with “convolution neural networks (CNN)”.

Research [15] presented the categorization of white blood cells employing both conventional image processing methods and DL techniques. Research [16] examined the Oriented FAST and Rotated BRIEF (ORB) feature extraction strategy against other pre-processing methods. Their research could be expanded by employing DL methods like modified convolutional neural networks. Optimization could be accomplished by quantum computing and adaptive algorithms for feature selection post-feature extraction.

3. Methods

The collected data is pre-processed by Global Contrast Normalisation (GCN). The pre-processed data is utilized with the Red Deer optimized Adaptive K-Nearest Neighbour (RD-AKNN) approach for image processing in computer networks. Fig 1 shows the overall flow of RD-AKNN.

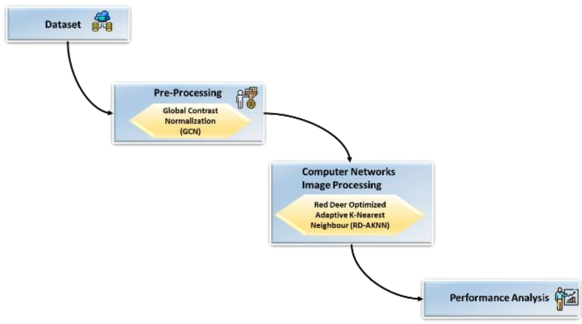

Fig 1. Overall flow of RD-AKNN

3.1 Image pre-processing using Global Contrast Normalization (GCN)

Global Contrast Normalisation (GCN) is an important phase of pre-processing in image-processing models for computer networks, enhancing the model's robustness and effectiveness. GCN attempts to standardize the contrast across the image to prevent the dominance of specific intensity levels and improve the model's ability to identify crucial features. The GCN method can be mathematically described below in Equation (1),

$$w'_{j,i} = \frac{w_{j,i} - \mu}{\sigma} \qquad (1)$$

Where,

μ - Standard deviation,

σ - Mean intensity of the whole image and

$w_{j,i}$ - Pixel intensity at position j, i in the image.

The normalized image w' is used as input for additional phases of the computer network to enhance learning and extracting features. Integrating GCN improves the model's capacity to adjust to changes in lighting conditions and enhances its overall generalization abilities.

3.2 Image processing in computer networks using Red Deer optimized Adaptive K-Nearest Neighbour (RD-AKNN)

3.2.1 Red Deer Optimization

The new method, similar to earlier evolutionary algorithms, commences with an initial collection of “Red Deers (RDs)”. Among the selected population, the best RDs were males, while the others were called female deers. After displaying aggressive behaviour, we establish harems (HA). A HA is a group of female deer. The population's hierarchical attributes are allocated among “Male Red Deers (MRD)” based on their proficiency in roaring and fighting, as well as their strength and elegance. The power and grace of MRD are directly related to their fitness value in genetic algorithms, with an inverse proportionality.

Roaring MRD is a way to improve them, performing as a solution in local searches around. MRD engages in battle against other MRD. Two males engage in the battle to choose a superior individual based on their respective values, with the winner advancing to the next level. After competing and demonstrating dominance, MRDs split all HAs among themselves. The male commander (MC) of the HA is mating with some of the female deer in his HA. The MC consistently mates with some of the female deers in each other's HA. Mating with the neighbouring female deer refers to mating with the female deer that is closest to the male in RDO. During this procedure, new solutions are created similar to the offspring of RD in a generation.

The RDO, like other meta-heuristic algorithms, consists of two stages, namely intensification and diversification. During the intensification phase, two males engage in a fight to determine the superior individual, to improve them. The male mates with the closest female deer in the nearby areas. A percentage of the female deers in an HA are randomly mated with roaring MRD as part of diversification. Intensification and diversification occur in addition to the mating of the MRD with female deers in his HA.

Stage 1: Developing the initial RDs

The purpose of optimization is to identify the most favourable solution based on the variable of the issue. We create a collection of variable values for optimization. The array is called a *chromosome* in the framework of genetic algorithms, however, in this case, it is designated as RD. Thus, RD is the equivalent solution. In an M_{var}-dimensional optimization issue, an RD is represented as an $1 \times M_{var}$ array. This array is specified as shown in Equation (2),

$$Red\ Deer = [w_1, w_2, w_3, w_{M_{var}}] \qquad (2)$$

Additionally, every RD's function value can be assessed as shown in Equation (3),

$$Value = e(Red\ Deer) = e(w_1, w_2, w_3, w_{M_{var}}) \qquad (3)$$

The initial population of size M_{pop} is created by the optimization algorithm at the beginning. The best RDs are chosen for M_{male}, while the others are chosen for M_{hind}.

Stage 2: Roar MRDs

During this stage, MRD are attempting to enhance their grace through roaring. If MRDs outperform the prior models concerning "objective functions (OFs)", they will replace them. We allow every MRD to modify its location. MRD roar to attract females.

Stage 3: Choose γ percent of the best MRDs to serve as MCs

There are significant differences among MRDs. Some are more successful than others. Males do not hold the same place in nature; some of them grasp HAs. MRDs are categorized into two types namely MCs and stags. The number of commander males is associated with γ and can be expressed as in Equation (4).

$$M.male.com = round\{\gamma . M_{male}\} \qquad (4)$$

$M.male.com$ represents the number of males capturing the HAs. We designate this MRD as the superior MRD, whereas the others are referred as stags. The number of stags is calculated as shown in Equation (5),

$$M.stag = M_{male} - M.male.com \qquad (5)$$

$M.stag$ represents the number of stags in the male population.

Stage 4: The battle between stags and MCs

We allow MCs to randomly battle stags. Select the individuals following the battle if the OF surpasses the previous ones.

Stage 5: Create Has

First off we create the HAs in this stage. A HA is a group of female deer that a dominant male is capturing. The size of HAs is determined by the dominance of MCs, which is influenced by their skills in roaring and fighting. To establish the HAs, we distribute female deer among MCs in proportion and we determine the standardized value of an MC as shown in Equation (6),

$$U_m = u_m - \max\{u_j\} \qquad (6)$$

Where, u_m - Value of m^{th} as a MC,

U_m - Normalized value (NV).

The “normalized power (NP)” of every MC is defined by having the NV of all MCs displayed in Equation (7).

$$O_m = \left| \frac{U_m}{\sum_{j=1}^{M.male.Com} U_j} \right| \qquad (7)$$

The NP of an MC is the proportion of female deers that should be possessed by that male. Subsequently, the amount of female deer in a HA will be shown in Equation

(8).

$M.harem_m = round\{O_m.M_{hind}\}$(8)

$M.harem_m$ represents how many female deer are in the HA of m^{th} and M_{hind} represents the total number of female deer. To distribute the female deers among the MCs, we randomly select female deers and assign them to each commander. These females, along with the males, will create a HA.

Stage 6: Mate the dominant male in an HA with $\propto$ the percentage of females in his group

The mating activity commences in step 5. We have modelled this phenomenon as a crossover in genetic algorithms. The MC and the female deer in his group are the parents. Their offspring are the novel solutions. The amount of female deer in an HA that mate with their MC is connected with the variable $\propto$ shown in Equation (9).

$$M.harem_m^{mate} = round\{\propto .M.harem_m\} \quad (9)$$

The number of female deers in m^{th} HA that are prepared to mate with these male RD is represented by$M.harem_m^{mate}$. We select $M.harem_m^{mate}$ at random from the $M.harem_m$.

Stage 7: Mate MC of the HA with β percentage of female deers in another HA

The MC is permitted to mate with the β female deer percentage of these HAs after we randomly select one HA. To establish his domain, the MRD ambush another HA. When a HA of RD mates with one male, the number of female deers involved is displayed in (10),

$$M.harem_m^{mate} = round\{\beta .M.harem_m\} \quad (10)$$

Where $M.harem_m^{mate}$ is the amount of m^{th} HA female deers that are prepared to mate with a single MRD. We also select $M.harem_m^{mate}$ of the $M.harem_m$ at random.

Stage 8: Stag mate with the closest female deer

During this stage, every stag mates with the nearest female deer. During the breeding period, MRD seems to prefer following a particular female deer, which can be his favourite among all the female deer. This male deer may be in his HA or may be associating with another HA. We let each MRD mate with the closest female deer. Each MRD has the opportunity to mate with at least one female deer, ensuring that each female deer mates at least once in the worst-case scenario. To determine the nearest female deer, we must estimate the distances between all female deer and every stag. We behave as though we are using a 2-dimensional strategy. The following formula is used to compute the separation in I-dimension space among an MRD and all female deers are shown in Equation (11).

$$c_j = \left(\sum_{i\epsilon I}(stag_i - hind_i^j)^{\,2}\right)^{1/2} \quad (11)$$

Stage 9: Choose the next generation

We chose the most suitable MRD for the next generation and selected female deers through roulette wheel selection, tournament selection, or other evolutionary mechanisms depending on their fitness.

Stage 10: Convergence

The stopping criterion might be determined by the number of epochs, the quality of the current finest solution, or a specified time interval.

3.2.2 K-Nearest Neighbour (KNN)

KNN was recognized as the most widely used and significant algorithms. KNN is recognized for its simplicity and ease of use. KNN is a kind of instance-based learning. This method is classified as a slow learning strategy. KNN involves identifying the K objects the training data that are most similar to the objects in the latest or testing data. The Euclidean distance calculation is typically utilized to determine the distance across two testing and training objects as shown in Equation (12).

$$cwz = \sqrt{\sum_{j=1}^{m}(w_j - z_j)^{\,2}} \quad (12)$$

3.2.3 Adaptive K-Nearest Neighbour

The AKNN algorithm is an advanced version of the KNN algorithm with extra procedures and developments. The phases of AKNN are as follows.

- ***Perform the distance calculation***

The KNN method is a classification technique that relies on identifying the nearest object to the target object. The distance across two points is calculated by applying the Euclidean formula to the testing data point (z) and the training data point (w).

- ***The reliability of training data***

Validity is assessed by examining the number of points in all training data, where the closest neighbour to each data point impacts its validity as indicated in Equation (13).

$$validity = \frac{1}{K}\sum_{j=1}^{K} T(IbI(w), IbI(M_{j(w)})) \quad (13)$$

The function T calculates the similarity across point w and the j^{th} data from the closest neighbour is shown in Equation (14).

$$T(b,a) = \begin{cases} 1_{b=a} \\ 0_{b\neq a} \end{cases} \quad (14)$$

Weighted voting

The weight determined by the Euclidean distance is multiplied by the validity of each data point in the training set to determine the outcome of the weight voting procedure. Equation (15) is utilized in the AKNN approach to determine each neighbour's weighted vote.

$$X(w) = validaitas(w)w\frac{1}{c_{f+0,5}} \qquad (15)$$

3.2.4 Red Deer optimized Adaptive K-Nearest Neighbour (RD-AKNN)

The RD-AKNN design is a considerable development in computer network image processing. This innovative method integrates the KNN algorithm with a customized optimization approach influenced by the adaptive features of RD, resulting in a collective result for important image processing concerns in the network environment. The validity and resilience of the RD-AKNN have an expressive impact on its performance. This model executes data-driven evaluation by assessing the attributes of neighbouring data points, employing the essential functionalities of the AKNN algorithm. The distinctive optimization strategy of RD-AKNN is inspired by the RD's capacity to function well in tough situations.

To accomplish the best results under different network settings, RD-AKNN can update its parameters when the features of the input data change. This adaptability is especially beneficial for regulating different image datasets on computer networks, as conventional image processing approaches can be significantly afflicted by variables such as noise levels, resolution imbalances and modifications in network traffic.

4. Results

We tested the suggested techniques on the Python 3.11 platform. The techniques were demonstrated on an Intel i5 7th Generation laptop operating Windows 10 and with 8 GB of RAM. We gather 3000 computer network images from [17] which are evaluated using the proposed Red Deer optimized Adaptive K-Nearest Neighbour (RD-AKNN) method and existing "Convolutional Neural Network (CNN)" [18] and "Deep Convolutional Neural Network (DCNN)" [19] methods.

The F1-score measures the balanced means of recall and precision. It indicates a prominent balance between precisely identifying crucial data and ensuring that all essential tasks are accomplished. The F1-scores for the traditional CNN and DCNN approaches are 92.6% and 94.8%, respectively. Our suggested RD-AKNN strategy provides an F1-score of 98.3%, as shown in Fig 2. A high F1-score shows better performance in computer network image recognition.

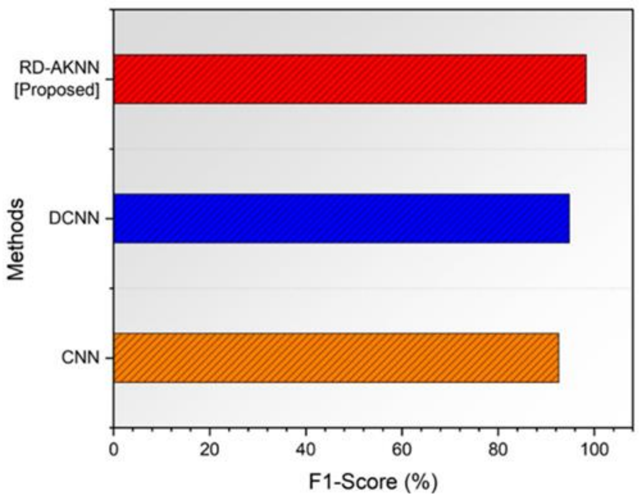

Fig 2. Result of F1-score

The accuracy of the model considers its ability to identify and evaluate images in network environments. The metric evaluated the ratio of correctly processed images to the total amount of images processed, showing the reliability of the model. The RD-AKNN method obtains an accuracy of 97.2%, surpassing the accuracies of CNN and DCNN methods, which are 92.4% and 96.3% respectively, as shown in Fig 3. A high accuracy score indicates consistency in processing different images, improving the model's effectiveness in network-related activities.

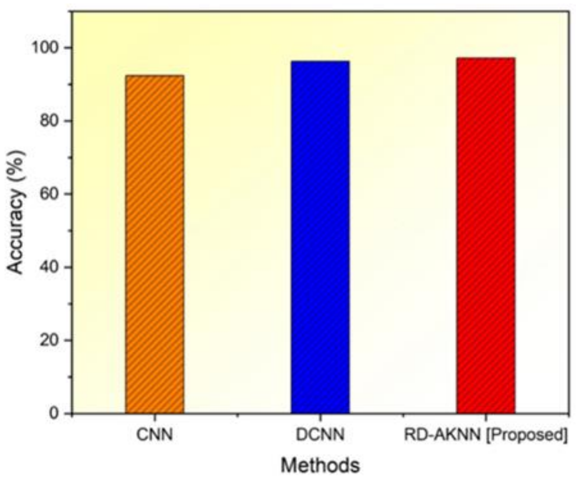

Fig 3. Output of accuracy

The recall is the proportion of correctly detected relevant images to all relevant images. Evaluating the system's ability to detect all relevant events properly while reducing false negatives. Evaluating the degree to which images are retrieved or categorized by algorithms in network-based applications is essential. As demonstrated in Fig 4, the RD-AKNN strategy obtains a recall rate of 97.5%, surpassing the recall rates of the CNN and DCNN approaches, which have 96.1% and 95.4%, respectively.

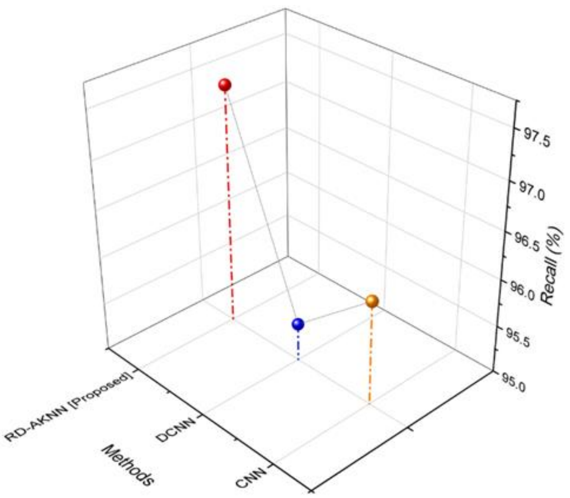

Fig 4. Result of recall

Precision evaluates the accuracy of pertinent information within retrieved images. It measures the proportion of relevant images that were correctly identified out of all the images obtained. When comparing the proposed RD-AKNN method with the existing CNN and DCNN methods which have the precision values of 94.5% and 93.3%, our proposed method achieved the precision value of 98.1%. Fig 5 shows the output of precision. High precision means having relatively few irrelevant images, which is important for using network resources efficiently and ensuring dependable information delivery. Table 1 displays the comparison output of RD-AKNN with existing approaches.

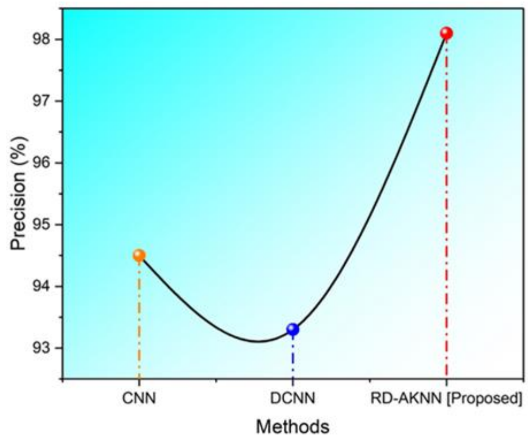

Fig 5. Output of precision

Table 1. Numerical outcomes of F1-score, recall, precision, accuracy

Methods	**F1-score**	**Recall**	**Precision**	**Accuracy**
CNN	92.6%	96.1%	94.5%	92.4%
DCNN	94.8%	95.4%	93.3%	96.3%
RD-AKNN [Proposed]	98.3%	97.5%	98.1%	97.2%

5. Conclusion

The combination of image processing and computer networks has become a significant force in the technological area, transforming the transmission, analysis and utilization of visual information. This study proposed an innovative machine learning-based model for processing image data in computer networks called Red Deer Optimized Adaptive K-Nearest Neighbour (RD-AKNN). The proposed approach is evaluated based on accuracy (97.2%), recall (97.5%), precision (98.1%) and F1-score (98.3%). This could struggle to generalize features in images that differ greatly from the training data distribution. This constraint could lead to unfavourable results when the model meets unseen or unusual image types. Future research could focus on investigating novel data augmentation techniques to introduce the model to a wider array of patterns and variations, hence decreasing its susceptibility to particular training data patterns.

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