Comparative Analysis of Kolmogorov-Inspired CNN and Traditional CNN Models for Pneumonia Detection: A Study on Chest CT Images

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Abstract: *Aim*: In this study, our goal is to compare the effectiveness of Kolmogorov Inspired Convolutional Neural Networks (KAN) with traditional Convolutional Neural Networks (CNN) models in pneumonia detection and to contribute to the development of more efficient and accurate diagnostic tools in the field of medical imaging.

Methods: Both models are structured with the same layers and hyperparameters to ensure a fair comparison of their performance. For a robust evaluation, the relevant dataset was divided into 80% for training and 20% for testing.

Results and Conclusion: Performance metrics of KAN; 95.2% sensitivity, 97.6% specificity, 94.1% precision, 96.9% accuracy (Acc), 0.9466 F1 score (F1) and 0. 9251 Matthews Correlation Coefficient (MCC), while the CNN model was found 92.5%, 96.4%, 91.2%, 95.3%, 0.9188 and 0.8858 for the same criteria, indicating that KAN outperformed. This comparison emphasizes that KAN has the potential to be a more effective model for pneumonia detection in chest CT images.

Keywords: Deep learning, Kolmogorov-Inspired Convolutional Neural Networks, Convolutional Neural Networks, Medical Imaging, Chest CT Images, Performance metrics.

1. INTRODUCTION

In recent years, artificial intelligence (AI) has emerged as a transformative force in medicine. This includes diagnosis, drug discovery, and prognosis prediction. Diseases are diagnosed using imaging, pathology, and/or laboratory tests. The products of this technology have been used intensively, especially in recent years, to minimize time loss, cost, and human error in these processes.

With the increasing availability of significant medical image datasets and advances in computational power, AI-assisted image processing techniques have shown great potential for accurate diagnosis and improved efficiency [1]. Deep learning models, especially CNNs, have been widely adopted for tasks such as disease detection and classification in radiology, pathology, and ophthalmology [2]. These models can provide accurate and timely decision support to healthcare professionals by analyzing complex patterns in medical images. AI in medical imaging not only reduces the workload of radiologists but also increases diagnostic accuracy by detecting subtle abnormalities that the human eye may miss. As a result, AI-driven solutions play a critical role in early diagnosis and personalized treatment plans, thereby improving patient outcomes and enhancing the quality of healthcare delivery [3].

Pneumonia, a severe respiratory infection, remains a leading cause of death worldwide, particularly among vulnerable populations such as children and the elderly. Accurate and timely diagnosis is essential to prevent serious complications. One of the most common diagnostic tools for pneumonia is chest imaging, particularly chest computed tomography (CT) scans, which provide detailed information on lung pathology. Deep learning techniques enable the automatic detection of pneumonia from chest CT scans and have attracted considerable attention in recent years due to the ability of these models to provide fast and accurate diagnosis [4].

Among image classification methods, CNNs are highly effective due to their ability to automatically learn spatial hierarchies from images [5]. CNNs have shown significant success in medical image classification, including pneumonia detection [6]. However, research is still ongoing to improve the performance of CNNs using advanced architectures inspired by mathematical models and theories. One such innovative approach is KAN, which integrates principles from Kolmogorov's superposition theorem to reduce the complexity of traditional CNNs and improve their generalization capabilities.

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In this study, KAN and CNN models were developed for the classification of healthy and pneumonia patients using chest CT images. All layers and hyperparameters, including the parameters of the CNN and KAN layers, are chosen in the same way so that the two different models can be used on the same dataset (80% for training and 20% for testing) to evaluate the model performance robustly. Our goal is to compare the effectiveness of KAN with traditional CNN models in pneumonia detection, thus contributing to more efficient and accurate diagnostic tools in medical imaging.

In our study, Section 2 explains the data source, the details of the KAN and CNN models used, and the performance evaluation metrics in detail. Section 3 presents the experimental results. Finally, Section 4 presents the conclusions and discussion of the results, compares the results with the existing literature, and provides recommendations for future work.

2. MATERIALS AND METHODS

This section explains in detail the data source used in the study, the details of the applied KAN and CNN models, and the performance evaluation metrics.

2.1. Deep Learning Models

Deep learning has revolutionized the field of artificial intelligence in recent years, leading to significant advances in processing and modeling complex data. Deep learning models, typically consisting of multiple layers, automatically learn abstract features in data and make inferences. CNN, one of the most widely used areas of this technology, provides successful results in many different fields, especially in image processing and computer vision problems. Due to their efficiency in processing image data, CNNs show strong performance in face recognition, object detection, medical imaging, and many other areas [7].

The basic structure underlying the success of CNNs is the ability to recognize complex patterns by processing input data through filters at different resolutions [8]. These networks learn the spatial relationships of the data through local connections and shared weights. For example, KANs, which recognize features such as edges, corners, or textures in an image and combine this information in deeper layers to make sense of objects or scenes, have emerged as an alternative to the classical CNN structure and take their mathematical foundations from Andrey Kolmogorov's functional approaches. KANs aim to reduce model complexity and improve data representation, primarily based on functional a priori. Kolmogorov's theorem states that simple functions can represent any continuous function in a specific piecewise form. KAN structures based on this principle offer an innovative solution to reduce computational costs while increasing the learning capacity of deep learning models. This provides an alternative modeling approach to the disadvantages of CNNs, such as high data requirements and computational power [9].

KANs have the potential to achieve similar performance with fewer layers, providing increased efficiency, especially in data-intensive applications. In addition, these structures bring more mathematical clarity to the overall structure of deep neural networks, making it possible to create more reliable and explainable models. Kolmogorov-based approaches have an essential place in the future development of deep learning algorithms, especially in modeling complex functions [9].

In this study, KAN and CNN models were developed to classify pneumonia and healthy patients. The same architecture and hyperparameters were used to compare the models' performance.

The data set is divided into 80% training and 20% testing using the hold-out method. In addition, another 20% of the training set was used for validation. Thus, the performance of the models was monitored during both training and validation. All images in the dataset were resized to 224x224 pixels to fit the input layer of the models. The models were trained for 100 epochs using the ReduceLROnPlateau and Early Stopping methods to avoid the overfitting problem. During model training, the 'Adam' optimizer algorithm was selected for optimization, and 'binary_crossentropy' was used as the loss function. With this configuration, the goal is to achieve better model performance during the training process. Table **1** shows the reduceOnLR parameters, and Table **2** shows the earlystopping parameters.

Table 1: ReduceOnLR parameters

Monitor	Patience	Mode	Factor	Min_lr
val_loss	3	Auto	0.3	0.000001

According to Table **1**, the ReduceLROnPlateau method monitors the validation loss (val_loss) of the model and dynamically adjusts the learning rate if no improvement is observed. If the validation loss does not improve for three epochs (patience=3), the learning rate is reduced by 30% (factor=0.3). The direction of improvement is set automatically (mode='auto'). In this process of decreasing the learning rate, the minimum learning rate is set to 0.000001 (min_lr=0.000001). This strategy aims to reduce the risk of overfitting by learning the model in smaller steps.

Table 2: Parameters for an Early Stopping

Monitor	Patience	Restore_best_weights
val_loss	5	True

According to Table **2**, the Early Stopping method keeps the performance of the model under control by monitoring the validation loss (val_loss). If the validation loss does not improve for five epochs (patience=5), the training process is stopped. This prevents overlearning and avoids unnecessary training. Furthermore, at the end of the training process, the best-performing weights are restored (restore_best_weights=True), thus preserving the best state of the model and making it ready for use.

Figure **1** shows the architectural details of the CNN and KAN models, which both CNN and Kolmogorov inspire.

Both CNN and KAN models, as shown in Figure **1**, aim to classify between two classes by processing the input RGB image data of 224x224 dimensions. First, three Conv2D layers are applied consecutively to extract the feature maps of the images, and MaxPooling layers are applied after each Conv2D layer to reduce the image size, preserve essential features, and reduce computational cost. Next, the data is made one-dimensional with a flattened layer, and two Dense layers allow the deep learning model to learn higher-level features. Finally, with two neurons and a sigmoid activation function in the output layer, the model generates probability values for each class, making a two-class prediction.

KAN extracts features from image data and processes them to perform two-class classification. In this structure, the KAN layers learn high-level representations of the images, while the MaxPooling layers provide dimensionality reduction and filter out redundant information. The flattened layer reduces the data to one dimension, and then two Dense layers learn the more complex features needed for classification. The sigmoid activation function in the output layer produces a probabilistic result between the two classes.

In the study, Acc and Loss graphs were obtained for training and validation datasets in CNN and KAN models. In addition, sensitivity, specificity, Acc, ROC, F1, and MCC were calculated to compare the performance of the test results of the models. This calculation was done using a confusion matrix, and pictures were obtained. ROC graph results are also presented.

Due to the dataset's imbalance, F1, which is the harmonic mean of precision and sensitivity and allows balancing these two metrics, was used. MCC, which calculates 1 as perfect classification, 0 as random classification, and -1 as complete misclassification, was also used, which provides a more useful evaluation in unbalanced datasets (Sarkar *et al*., 2023) [3].

2.2. Data Source

The open-source dataset used in our study consists of OCT (optical coherence tomography) and chest X-

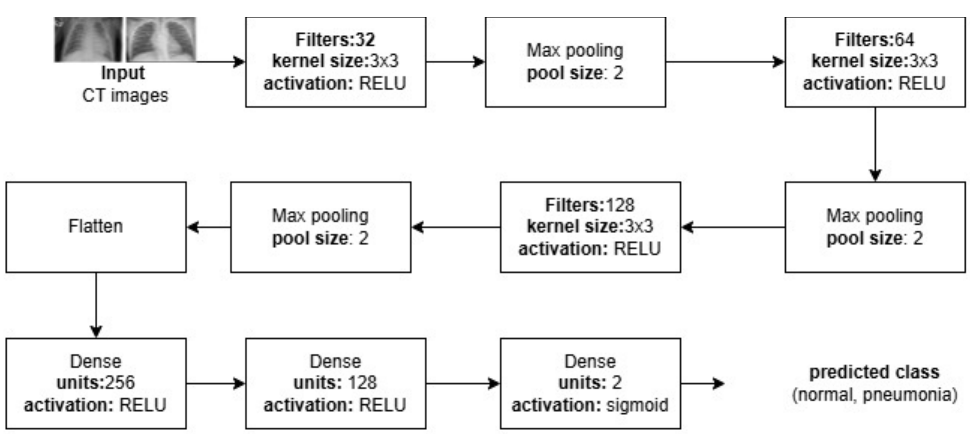
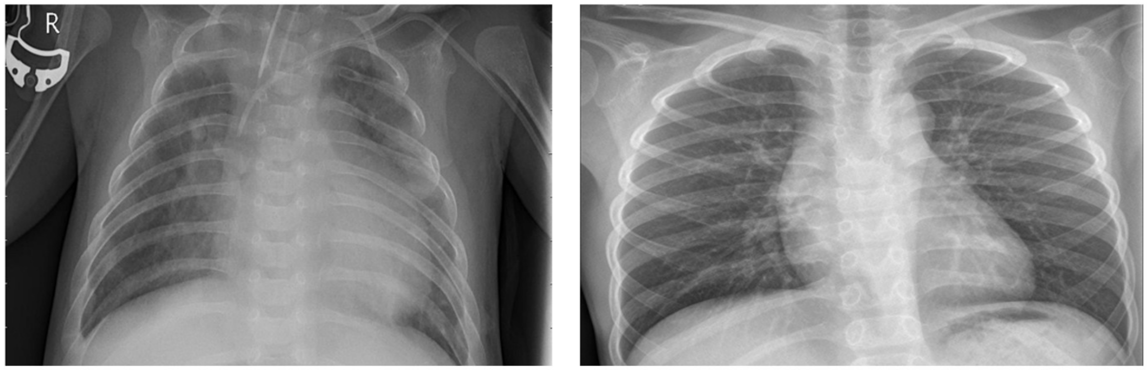


Figure 1: The model architecture used in this study.



a) b)

Figure 2: Dataset Sample Image **a**) Pneumonia **b**) Normal.

ray images. The OCT images are divided into training and test sets of independent patients, and each image is labeled as a “disease-randomized patient ID-image number.” The dataset also includes chest X-ray images to support the diagnosis of lung diseases [10]. From the CT images collected by the University of California San Diego [10], there are 1583 CT images labeled as Normal and 4273 CT images labeled as Pneumonia.

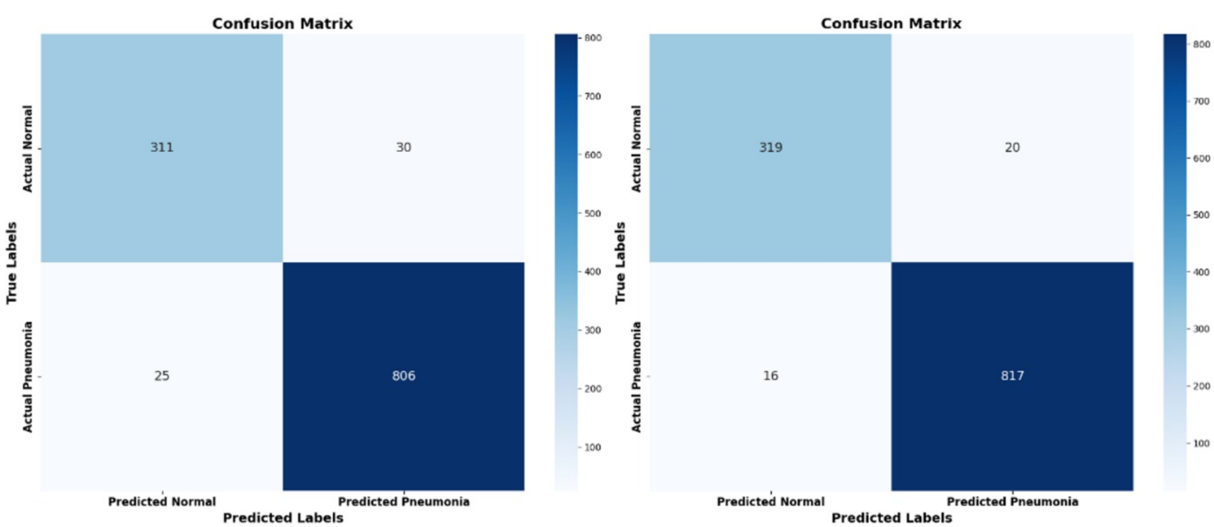
In this study, models were created using CNN and KAN to classify chest tomography data labeled as pneumonia and normal. Figure **2** shows an example of these two classes.

3. RESULTS

This section presents the performance results of the CNN and KAN models in detail. To evaluate the models' classification success, a confusion matrix, Acc graphs with training/test loss during the training process, ROC curves of the test dataset, and performance metric results are presented.

When evaluating the confusion matrix, according to the CNN model result, there are a total of 311 true positives and 806 true negatives. The misclassifications consist of 30 false positives and 25 false negatives (Figure **3a**). For the KAN model, the number of true positives was 319, and the number of true negatives was 817. The misclassifications consisted of 20 false positives and 16 false negatives (Figure **3b**).

Figure **4** shows the training and validation Acc charts. For the CNN model (Figure **4a**), it can be seen that the training accuracy increases continuously however the validation accuracy fluctuates and experiences significant drops at certain epochs. This indicates that the CNN model overfits the training data and loses its ability to generalize to the validation data



a) b)

Figure 3: Confusion Matrix **a**) CNN **b**) KAN.

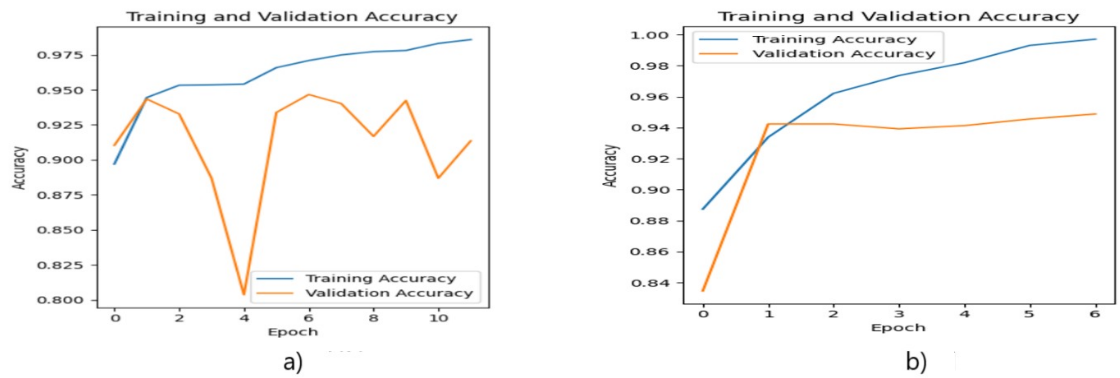


Figure 4: Training / Validation of Acc-Loss Charts **a**) CNN **b**) KAN.

set. This is also supported by the fact that the training accuracy is significantly higher than the validation accuracy. For the KAN model (Figure **4b**), the training and validation accuracies are more consistent. The training accuracy increases rapidly and approaches 1.0, while the validation accuracy increases steadily and stabilizes at a high value. This shows that the KAN model has better generalization performance on both training and validation data.

The AUC value of 0.99 for both CNN (Figure **5a**) and KAN (Figure **5b**) models supports the high classification success highlighted in the text. The ROC curves rise steeply at low false favorable rates and are close to 1, indicating that the models can successfully discriminate positive classes.

According to Table **3**, which shows the performance metrics of the CNN and KAN models on the test dataset, KAN outperformed CNN in every metric, especially in the metrics sensitivity, specificity, precision, Acc, F1, and MCC. KAN is more successful in discriminating against both positive and negative classes. The higher MCC indicates that the overall classification quality of the model is better.

4. DISCUSSION

In this study, KAN, which is not yet widely used and which has few studies [1, 4, 6, 11-15]. The performance of KAN and CNN models in image classification has been evaluated using various metrics such as sensitivity, specificity, precision, Acc, F1, and MCC. According to the results, it can be stated that the

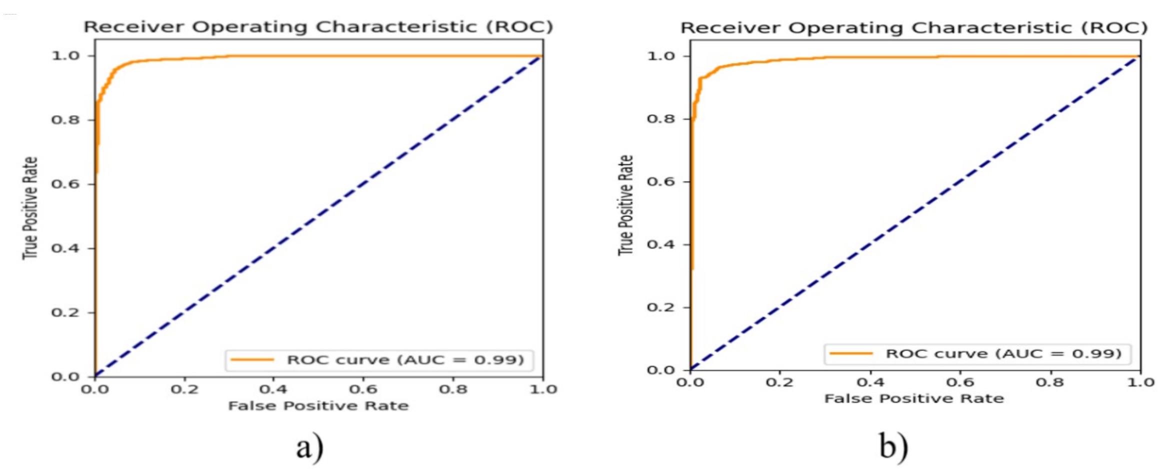


Figure 5: ROC Graph **a**) CNN **b**) KAN.

Table 3: KAN and CNN Modeling Performance

	Sensitivity	Specificity	Precision	Acc	F1	MCC
CNN	0.9256	0.9641	0.9120	0.9531	0.9188	0.8858
KAN	0.9522	0.9761	0.9410	0.9693	0.9466	0.9251

KAN model has a lower error rate, higher classification success, better fit to the data, and better generalization ability due to its robustness to the overfitting problem.

When the results obtained from image classification studies using different models are examined, Rohmah & Bustamam (2020) [16] combined Local Binary Pattern, HOG, and Gray Level matrices for feature extraction in CT and X-ray images for COVID-19 classification. Principal Component Analysis (PCA) and Support Vector Machine (SVM) were used for feature reduction and classification, respectively. By combining the feature extraction approaches, they achieved 99% and 97% accuracy for CT and X-ray images, respectively.

Wang, *et al*. (2021) [17] used a dataset of 1065 CT images to detect Covid-19 using an inception transfer learning algorithm. In their research, the highest accuracy rate was 89.5%, and they concluded that this rate is proof that artificial intelligence is a precise tool in radiological feature extraction in COVID-19 detection.

Türkoğlu (2021) [18] created a multiple kernel ELM-based MLP architecture to detect COVID-19 through deep feature extraction using the DenseNet201 network. The network architecture in this study performs better than other existing architectures, with the highest accuracy rate of 98.36%.

Inspired by Kolmogrov-Arnold theory, Liu *et al*. proposed KANs as an alternative to multilayer perceptrons (MLPs) and showed that the model theoretically has faster neural scaling than MLPs. They also applied the KAN model to a toy dataset and a Feynman dataset and obtained the highest Acc of 84% on these datasets [15].

Wang *et al*. compared the performance of multilayer perceptron (MLP) and KAN models with the same network settings, using the images of 10 subjects for training from CEST MRI data of 12 healthy volunteers. They found that the CEST agreement metric produced by the KAN model had a higher Pearson coefficient than the MLP models [14].

Indicating that KANs have become a promising alternative to traditional MLP methods, Bresson *et al*. built KAGNN models by adding layers to graphical neural network models used in standard graphical learning. They compared the Graphical Isomorphism Network model, a standard graphical classification method, with the KAGNN model they created by adding a Kolmogorov-Arnold layer on seven different data sets. They obtained the highest accuracy results with the 85.45% KAN model on the MUTAG dataset [13].

Herbozo *et al*. presented their KANEEG model, which was designed explicitly for effective seizure detection using EEG data from adult epilepsy patients from three different continents. By comparing the KAN model with traditional MLP models, Herbozo *et al*. showed that although the metrics of both models are at a high level, the KAN model provides significant generalization across datasets from different regions and has higher efficiency. In their proposed KANEEG models, they used the TUH (USA) dataset of adult epilepsy patients for validation and training and the Epilepsia and RPAH datasets as tests for effective seizure detection. Validation on the TUH dataset yielded an AUC of 0.889 and F1 of 85.1, while the RPAH test dataset yielded an AUC of 85 and the Epilepsia test dataset an AUC of 78. They also emphasized that the KAN architecture is robust to size reduction and modeling of shallow network structures and has breakthrough potential in medical diagnostics [12].

Finally, Patel *et al*. compared the performance of CNNs and Graph Convolutional Networks (GCNs) by applying an integrated convolutional KAN to convolutional layers in their classification study on Parkison's Progratio Markers Initiative (PPMI) dataset. In their results, they found that KANs had the highest AUC (99%). They also demonstrated the importance of KANs in detecting PD and capturing subtle brain changes [11].

The improvement in sensitivity and accuracy suggests that KAN is particularly effective in reducing both false negatives and false positives. Examination of the Acc and F1 metrics shows that the model is able to achieve a higher overall correct classification rate while maintaining a balance between precision and recall. The higher MCC rate highlights KAN's robustness in dealing with unbalanced data and its ability to provide reliable performance in different scenarios [19].

These results suggest that the KAN model, with its advanced architecture, is better suited for complex classification tasks where traditional CNN models may struggle to maintain high accuracy and correct class separability. Future research could explore further optimizations, such as incorporating different regularization techniques or hybrid approaches to KAN, to further improve its performance in real-world applications.

The overall improvement observed with KAN highlights the importance of considering alternative neural network architectures to improve model accuracy, especially in challenging classification tasks.

DECLARATION STATEMENTS

As the data is open source, there are no experiments on humans conducted by the authors. Open source has been studied on CT images.

CONFLICT OF INTEREST

The authors declare no conflicts of interest.

CONSENT TO PUBLISH

Authors affirm there is no figure of any participant in the article.

AUTHOR CONTRIBUTIONS

Defining the methodology, data analysis, experiments and evaluations, manuscript draft preparation

DATA AVAILABILITY

The dataset is shared open source. Availability: Kermany, Daniel; Zhang, KANg; Goldbaum, Michael (2018), “Labeled Optical Coherence Tomography (OCT) and Chest X-Ray Images for Classification”, Mendeley Data, V2, doi: 10.17632/rscbjbr9sj.2

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