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Deep Learning Based Multi-Parameter Assistive System for COVID-19 Diagnosis

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ABSTRACT

Epidemics like the COVID-19 epidemic are major global problems, some of which spread rapidly, causing high mortality rates. The rapid spread of such diseases leaves behind the production and global use of medical testing tools, and during this period, the undetected disease spreads quickly and becomes hard to control. Therefore, non-medical digital technologies with faster disease prediction are needed. The studies on deep learning, a subfield of artificial intelligence, reveal that it is possible to predict disease more quickly. It will be possible to stop the pandemic progress with minimal damage if the best predictive approach is used. Lives are saved when the disease is detected early. A dataset containing low-dose CT scan images, gender, age, weight, COVID-19 PCR test result, and symptoms including cough, fever, shortness of breath, chest pain, and fatigue were used in this study. The primary goal is developing an assistive system for diagnosing COVID-19 disease based on deep learning using this dataset. The deep learning technique used in this study has a multi-branch architecture consisting of both classical artificial neural networks and convolutional neural networks. As a result of this study, it was concluded that the developed technique can be used not only for COVID-19 but also for different diseases and is open to development with data from more patients.

1. Introduction

COVID-19 disease first appeared in Wuhan which is a city in China in December 2019. The disease spread worldwide, leading to the pandemic caused by a virus called SARS-CoV-2 [1, 2]. Typical symptoms of COVID-19 include headache, cough, fever, fatigue, a loss of smell and taste, and breathing issues. Multiple diagnostic tests have been created to identify COVID-19. These testing methods can also give misleading results. More precise chest imaging can, nevertheless, yield the desired outcome. At the same time, in the chaos of the pandemic, the need for faster examination and diagnosis of chest imaging data has emerged. Artificial intelligence is now successfully applied in medical disease and diagnosis. While it takes years of medical training and real case experience to correctly interpret a medical image, artificial intelligence does this for us in a much shorter time and by seeing more cases than a medical professional can. An artificial intelligence algorithm called convolutional neural networks provides very successful results, especially on digital image datasets, compared to other artificial intelligence algorithms. In this study, it has been studied how deep convolutional neural network algorithms, which give effective results on chest X-ray datasets, can achieve the same classification on medical images with anatomical differences such as chest CT.

Chest CT scans can be used as a highly accurate routine control tool in epidemic areas, according to Zeng et al. [3]. However, COVID-19 scans can expose them to both costly and unnecessary radiation doses. Standard chest CT scans have a radiation dosage of around 4.7 mSv, whereas chest X-rays have a radiation exposure of approximately 0.05 mSv. Using a hybrid model of traditional signal processing and deep learning techniques, chest CT scans seem to outperform chest X-rays [4]. The author speculated that this may be because chest CT scans have less amount of chest ribs and diaphragms compared to chest X-ray images. In [5], although there are injuries whose clinical significance is uncertain, it has been shown that more injuries can be detected with CT than with normal radiography in patients with blunt trauma. However, in patients with blunt trauma, first a normal chest X-ray and then a chest CT are performed to detect injuries. Gezer et al. [6], concluded that chest CT may be more appropriate in non-traumatic cases presenting to the emergency department, depending on old age and supine position. As in this study [7], it is thought that techniques such as low radiation

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dose chest CT may be the most logical option for the available data. On the other hand, chest CT is used in the diagnosis of other diseases such as breast cancer. For instance, Desperito and others [8] have obtained remarkable diagnostic results using chest CT data.

In the literature, COVID-19 is mainly classified based on chest X-ray images. Using a model called EfficientNet, Marques and others obtained accuracy scores of 96.70% in the triple classification as COVID-19, pneumonia, non-findings, and 99.62% in the binary classification as COVID-19, non-findings, on medical chest X-ray images [9]. Ozturk and her colleagues reached 87.02% accuracy scores in the multi-class classification as COVID-19, pneumonia, non-findings, and 98.08% in the binary classification as COVID-19, non-findings using a model called Darknet on chest X-ray images [10]. Using a model called VGG-19, Vaid and others achieved a 96.3% accuracy score by binary classifying chest X-ray scans as COVID-19 and non-findings [11]. Apostolopoulos and Mpesiana studied two different datasets using models named VGG-19 and MobileNet v2. In the first dataset they used, with the model named VGG-19, they obtained 93.48% in the 3 multi-class classification of COVID-19, pneumonia, non-findings, and 98.75% in the binary classification of COVID-19 and non-findings. Also by using the model named MobileNet v2, they achieved 92.85% in 3 multi-class classifications and 97.40% in binary classification. In the second dataset, they used, using only the model named MobileNet v2, an accuracy score of 96.78% for binary classification and 94.72% for 3 multi-class classifications was obtained [12]. Using a transfer learning model called nCOVnet, Panwar and his colleagues also achieved an accuracy score of 88.10% by binary classification of medical chest X-ray images, such as COVID-19 and non-findings [13]. Using a model called CapsNET, Toraman, and his friends achieved an accuracy score of 84.22% by making multi-class classifications like COVID-19, pneumonia, and non-findings, and a 97.24% accuracy score by making binary classification in chest X-ray images [14]. Perumal and others achieved an accuracy score of 94.3% by making multi-class classifications such as COVID-19, pneumonia, and non-findings on medical X-ray images using a model called INASNET [15]. The study published by Mahin and his colleagues in 2021 demonstrated the effectiveness of deep transfer learning techniques by achieving accuracy rates of 98% with MobileNetV2, 96.92% with InceptionV3, 94.95% with EffNet, and 92.82% with VGG19 in identifying COVID-19 and pneumonia [16]. In the study in [17], five different deep learning models such as ResNet50, ResNet101, DenseNet121, DenseNet169, and InceptionV3 were used to recognize COVID-19 from chest X-ray images, and the ResNet101 model exhibited the best performance with 96% accuracy, precision, and sensitivity rate. The multi-objective differential evolution-based CNN model developed to classify COVID-19 patients using chest CT images in [18] achieved 1.9789% higher accuracy, 2.0928% higher F-measure, and 1.8262% higher accuracy than competitive models. It showed superior performance with higher sensitivity, 1.6827% higher specificity, and 1.9276% higher Kappa statistic. Sufian and others evaluated deep learning models that classify COVID-19 using three-channel grayscale CT images and achieved 99.60% accuracy and 99.59% recall with the InceptionV3 model [19].

In this paper, developed a deep learning model for diagnosing COVID-19 disease using a dataset containing images of low-dose CT scans, gender, age, weight, COVID-19 PCR test result, and symptoms including cough, fever, shortness of breath, chest pain, and fatigue. The developed deep learning model can be used as an auxiliary system that can assist medical professionals.

2. Material and Method

2.1. The Used Clinical COVID-19 Dataset

In this study, we used a dataset called COVID-19 Low-Dose and Ultra-Low-Dose CT Scans for COVID-19 detection [20]. This dataset has been published on a machine learning and data science community platform called Kaggle [21]. However, there is no information about which clinics and countries the data were collected from. This dataset contains data from 160 different patients. For each patient, data is available in the form of low-dose CT scan images, gender, age, weight, COVID-19 PCR test result, and 5 different symptoms: cough, fever, shortness of breath, chest pain, and fatigue. A section from the dataset is included in Table I. While the images in Fig. 1 belong to CT scans of COVID-19 patients with ID C001, the ones in Fig. 2 belong to CT scans of non-COVID-19 patients with ID N001.

Table 1. A section containing the data of four patients from our dataset.

Id	Gender	Age	Weight	Cough	Fever	Dyspnea	Chest Pain	Fatigue	PCR	Result
C001	Male	51	80	No	No	No	No	No	Yes	COVID
C002	Female	68	75	No	No	No	No	No	Yes	COVID
N001	Female	22	80	Yes	No	No	No	No	N/A	Non-COVID
N002	Female	19	98	No	No	No	Yes	No	N/A	Non-COVID

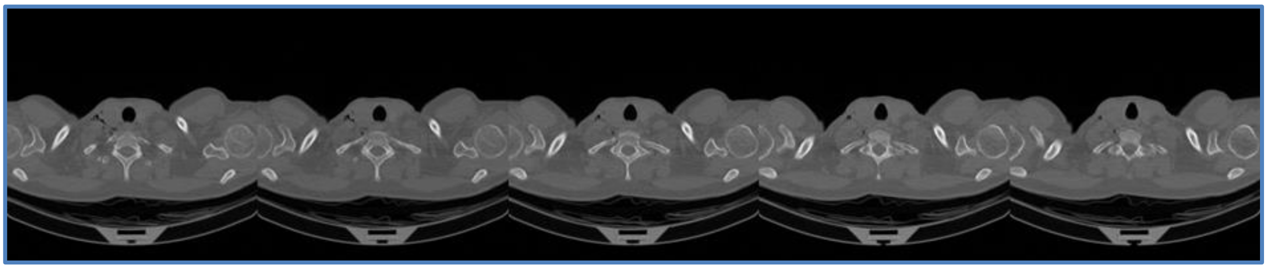

Fig. 1 The CT scans of COVID-19 patient with ID C001.

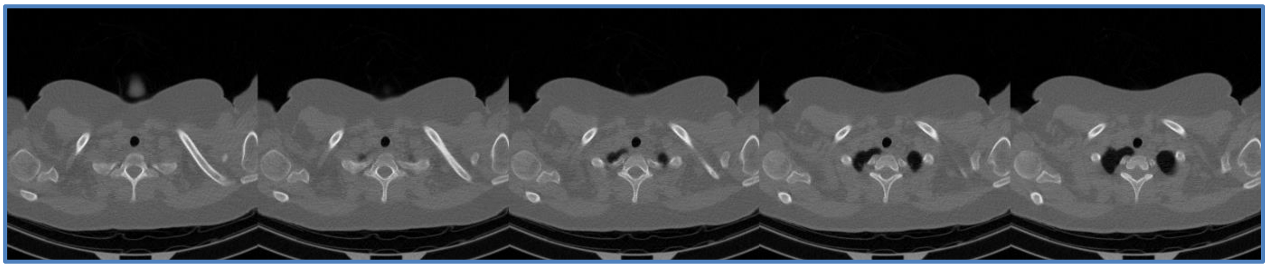

Fig. 2 The CT scans of non-COVID-19 patient with ID N001.

2.2. The Developed Deep Learning Model

Artificial intelligence (AI), especially a computer system that integrates human intelligence functions; Learning is defined as the ability to imitate features such as drawing logical conclusions, perceiving information from the environment, understanding language, and problem-solving [22]. Machine learning is a branch of artificial intelligence developed to enable machines to perform tasks by learning directly from experience rather than from programmed information [23]. Deep learning is a machine learning technique that uses multi-layered structures to learn data representations and outperforms traditional machine learning algorithms, especially on large amounts of data [24]. Artificial neural networks (ANN) are computational systems created by modeling the way the human brain processes information, and they are especially effective in pattern recognition and classification tasks [25]. Convolutional neural networks (CNN) are widely used in the image processing industry and enable automatic learning of relevant features by applying local convolution operations on large images [26].

In this study, a new neural network architecture was developed that combines both numerical and image data processing capacities of artificial neural networks. This new architecture has a multi-branched structure with different architectures in each branch. While convolutional neural networks (CNN) are preferred in the branch where image data is input, classical artificial neural networks are preferred in all other branches that receive numerical input. Fig. 3 shows the model plotting graphic of the developed new architecture.

The first branch of this newly developed architecture receives image inputs and has a convolutional neural network structure. The convolutional neural network structure in this branch consists of two convolutional layers, two maximum pooling layers, a flattened layer, and two dense layers also called fully connected layers. The use of convolution layers allows us to extract more features from images. The max-pooling layers are used to solve the overfitting problem by reducing the number of parameters. The dense layers are found in the final parts of convolutional neural networks to optimize goals such as classification scores. Fig. 4 presents a graphical representation of the architecture of the used convolutional neural network.

The other branches of the newly developed architecture receive numerical data input and have a classical artificial neural network structure, which consists of only dense layers. Each of these other branches contains two dense layers whose activation function is the rectified linear unit (ReLU). The number of units in the first layer of the artificial neural networks in this branch that take gender and PCR test data as input is 8, those that take age and weight data as input are 16, and those that take symptoms as input are 32. The number

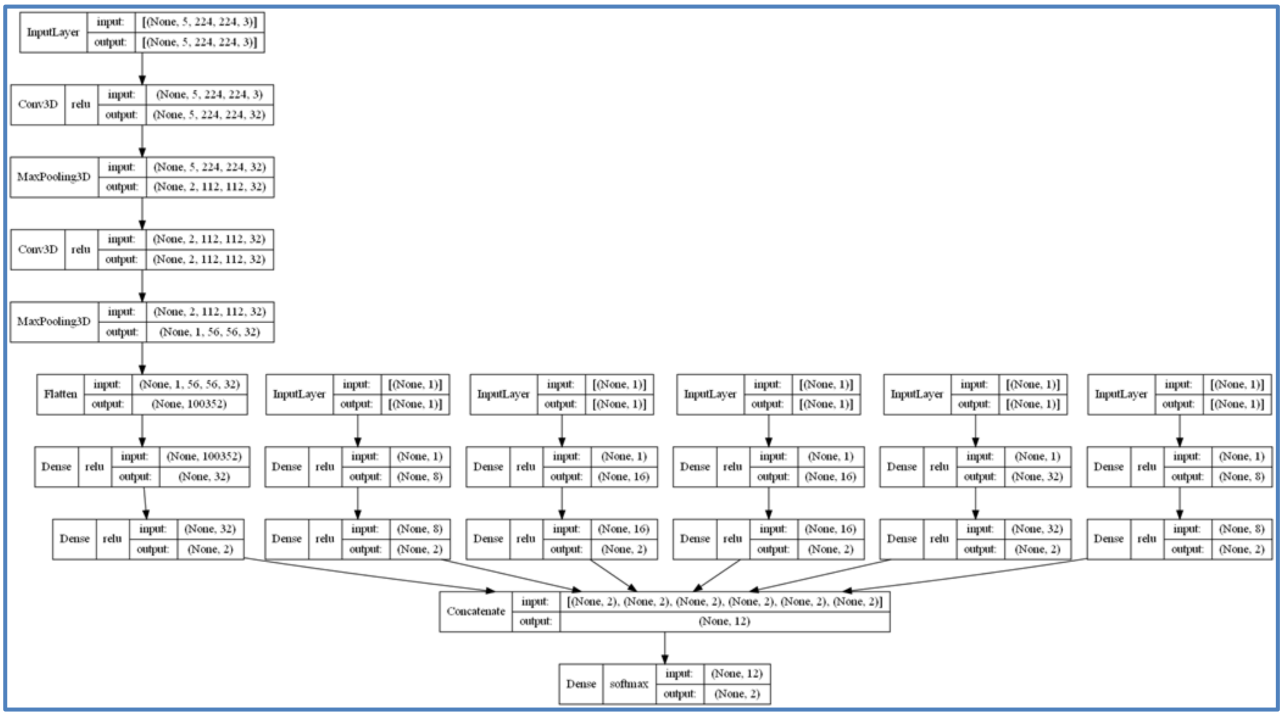

Fig. 3 The model plotting graphic of the developed new architecture.

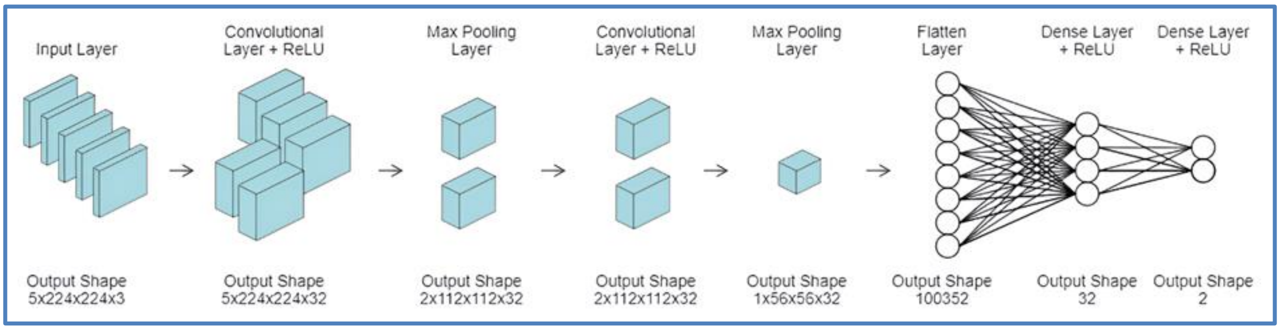

Fig. 4 A graphical representation of the architecture of the used convolutional neural network.

of units in the last layers of these branches is 2. The graphical representations of the artificial neural network architecture in these branches are shown in Fig. 5.

2.3. The Development Environment

A development environment has been created where different models are designed, implemented, and undergo training, validation, and testing processes. A couple of software elements such as Python, Keras, and Google Colab were used to create this development environment. Python is a multi-purpose programming language that is frequently used in artificial intelligence and deep learning [27]. Keras is an application development interface (API) for developing deep learning applications written in Python [28]. Google Colab is a free cloud-based Python programming environment with runtime options such as CPU, GPU, and TPU [29].

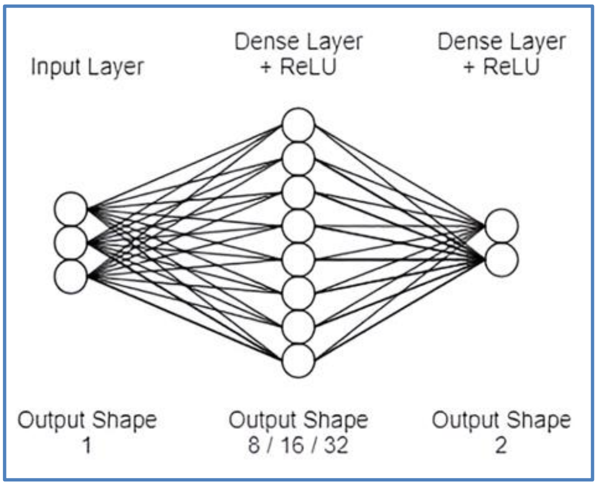

Fig. 5 A graphical representation of the architecture of the used classical artificial neural networks.

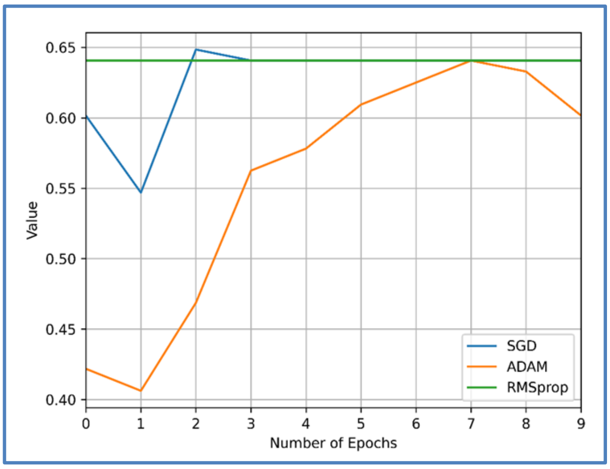

Fig. 6 The training accuracy values of different optimizer options over 10 epochs.

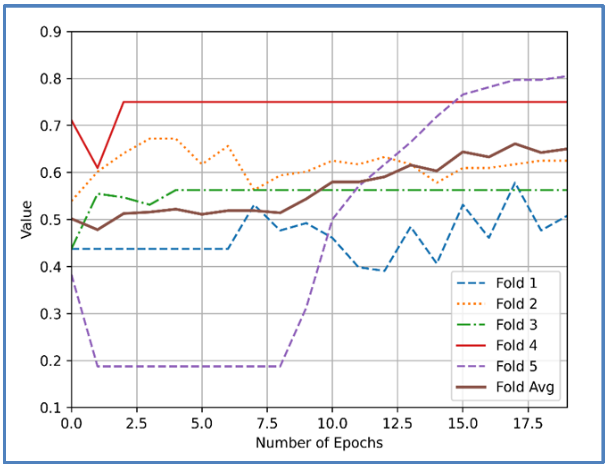

Fig. 7 The training accuracy values of 5-fold cross validation over 20 epochs.

3. Results and Discussion

We performed two different experiments to find the most accurate and most effective hyperparameters. While performing these experiments, we kept the values of some hyper-parameters constant and assigned different values to the values of other hyper-parameters, respectively. We have shown the accuracy results of these experiments on line graphs.

In the first experiment, our model went through a training process with different optimizer options to improve the results. Optimizers are used in training processes to determine the most appropriate weights in artificial neural networks. Therefore, the best optimizer option is the one that leads to the most optimal solution first. Stochastic gradient descent (SGD), adaptive moment estimation (ADAM), and root mean square propagation (RMSprop) were used as optimizer options, respectively. Figure 6 shows the training accuracy values of different optimizer options over 10 epochs. As seen in the graph, the RMSprop optimizer reached the optimal result from the first epoch, and the SGD optimizer reached the same optimal result after a few epochs. However, the ADAM optimizer reached the optimal result later than the others, but it does not have the stability to show the same results. It can be said that the best optimizer option for our model is RMSprop.

In the second experiment, we applied a 5-fold cross-validation process using RMSprop, the optimizer we chose. The reason why we apply 5-fold cross-validation is to understand which data range performs a better training process. Fig. 7 demonstrates the training accuracy results graphically for each fold and the average of all folds. As can be seen from here, the 4th fold accuracy started well at over 0.70 in the first epoch and continued by maintaining the accuracy value between 0.70 and 0.80 with the third epoch. The 5th fold had the lowest start, but at the end of 20 epochs, it reached an accuracy value of over 0.80, which is higher than the others. The average of all folds reached an accuracy value between 0.60 and 0.70 at the end of 20 epochs, and the accuracy values of other folds were close to these average values.

Table 2. The metric results of the final evaluation and all experiments according to different dataset combinations and model hyperparameters.

Dataset Selection	Model	Training Accuracy	Testing Accuracy
Random Select	Model with RMSprop	0.66	0.90
Random Select	Model with ADAM	0.64	0.68
Random Select	Model with SGD	0.64	0.71
Fold 1	Model with RMSprop	0.57	1.00
Fold 2	Model with RMSprop	0.67	0.40
Fold 3	Model with RMSprop	0.56	1.00
Fold 4	Model with RMSprop	0.75	0.25
Fold 5	Model with RMSprop	0.80	0.09
Average of Folds	Model with RMSprop	0.65	0.63

As a result of these experiments, it was decided to choose the right artificial neural network hyperparameters and dataset combination that would yield the best results. A final evaluation is required after finalizing the model according to the best-decided hyperparameters and combination. In the final evaluation, the accuracy results were reviewed using the test dataset containing data that the model had not seen during training. Table 2 contains the metric results of the final evaluation and all experiments. According to both the training accuracy result 0.66 and test accuracy result 0.90 stated in the table, our model, whose optimizer is RMSprop, with a random training and test data set, is the most optimal artificial neural network solution we have achieved.

4. Conclusion

Studies in the literature regarding the diagnosis of COVID-19 disease were generally carried out through X-ray or CT scan images. The X-ray images are in only 2-dimensional space. However, CT images, whose long name is computed tomography, are more detailed. Therefore, the image data in our dataset are chest CT images. Other data in our dataset is the gender, age, weight, COVID-19 PCR test result, and symptoms including cough, fever, shortness of breath, chest pain, and fatigue of the patient to whom the pictures belong.

Fine-tuning the hyperparameters of deep learning models is important because it directly affects the results. We fine-tuned a deep learning model shaped multi-branches architecture consisting of convolutional neural networks and artificial neural networks. As a result of fine-tuning efforts, an optimizer called RMSprop reached the optimal result faster than other optimizer options. We preferred the categorical cross-entropy used in multi-class classifications as the loss function. The batch size, which is the number of training samples, is selected as 32. Depending on the hardware used, we decided end of training process on the 20th epoch, which is the point where the learning status of the model remains in a constant range.

To further improve the results, different hyperparameters and neural architectures can be tested with more powerful hardware. In fact, the results could have been better if more patient data had been used using more powerful equipment. However, with our existing dataset and the hardware within our minimum budget, we managed to design a deep learning model of average fitness for the multi-parameter COVID-19 assistive diagnosis system. We obtained an accuracy value of 0.66 in our training dataset and an accuracy value of 0.90 in our test dataset with this deep learning model we designed.

Declaration

Author Contribution: Conceive– M. A. Senturk; Design– M. A. Senturk, R. K. Tan; Experimental Performance, Data Collection and Processing– M. A. Senturk, R. K. Tan; Literature Review– M. A. Senturk, R. K. Tan; Writer– M. A. Senturk, R. K. Tan; Critical Review– R. K. Tan.

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