



# A Hybrid Convolutional Neural Network-Support Vector Machine for X-ray Computed Tomography Images on Cancer

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## Abstract

**BACKGROUND:** Cancer is a major health problem not only in Indonesia but also throughout the world. Cancer is the growth and spread of abnormal cells that have distinctive characteristics, that if can no longer be controlled will usually cause death. The number of deaths due to cancer is generally caused by late diagnosis and inappropriate treatment. To reduce mortality from cancer, it is necessary to strive for early detection and monitoring of cancer in patients undergoing therapy. Convolutional neural networks (CNNs) as one of machine learning methods are designed to produce or process data from two dimensions that have a network tier and many applications carried out in the image. Moreover, support vector machines (SVMs) as a hypothetical space in the form of linear functions feature have high dimensions and trained algorithm based on optimization theory.

**AIM:** In connection with the above, this paper discusses the role of the machine learning technique named a hybrid CNN-SVM.

**METHODS:** The proposed method is used in the detection and monitoring of cancers by determining the classification of cancers in X-ray computed tomography (CT) patients' images. Several types of cancer that used for determination in detection and monitoring of cancers diagnosis are also discussed in this paper, such as lung, liver, and breast cancer.

**RESULTS:** From the discussion, the results show that the combining model of hybrid CNN-SVM has the best performance with 99.17% accuracy value.

**CONCLUSION:** Therefore, it can be concluded that machine learning plays a very important role in the detection and management of cancer treatment through the determination of classification of cancers in X-ray CT patients' images. As the proposed method can detect cancer cells with an effective mechanism of action so can has the potential to inhibit in the future studies with more extensive data materials and various diseases.

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## Introduction

Cancer is a malignant disease due to the uncoordinated growth of abnormal cells in body tissues [1], as one of the health problems with the most deaths throughout the world, including Indonesia. The World Health Organization (WHO) states that cancer as the main causes of death inflicts around 13% of all causes of death throughout the world [2]. In 2007, there were an estimated of 7.9 million cancer deaths in the world, that each year about 12 million people of cancer sufferers conduce 7.6 million of them die from cancer worldwide [3]. If not restrained, by 2030, there will be 26 million cancer patients and 17 million cancer deaths [3]. Ironically, this event will happen more quickly in poor and developing countries like Indonesia. Based on RISKESDAS data, the proportion of cancer in Indonesia denoted an increase of 1.79 per 1000 population in 2018 from 2013 by 1.4 per 100 population [4]. The most common types of cancer that causes death every year are lung cancer with 1.4 million deaths/year followed by 653,000 deaths/year of liver cancer and 548,000 deaths/year of breast cancer [5]. Those types of cancers

are different between men and women, where for men are lung and liver as the most common type, while lung and breast are for women.

Lung cancer is the most common disease caused death that occurs when abnormal cells grow in lung tissue [6]. Lung cancer causes men to die more often than other cancers, as ranked six out of 10 main causes of death in Indonesia, where dominated with cigarette smoke as the lead elements. Surgery of thoracic is one of the primary solutions [7], yet still has many perils and ravel that can induce to death. Furthermore, including Indonesia, liver cancer is also big res throughout the world. If a person is exposed to chronic hepatitis, it can progress to liver cirrhosis and eventually liver cancer in 20–30% of cases [8]. One of the preventions is the treatment of chronic hepatitis which reduces liver inflammation by eliminating or suppressing the replication of the causative virus [9], but until now there is no optimal therapy. Finally, breast cancer is a disease where the malignant cells are in the breast tissue [10]. This cancer is the most common cancer suffered by women in developed countries, including Indonesia, which can have problems in the psychological aspect. The incidence of breast cancer continues to increase

and until now there have been no data that are sure to be the main cause of breast tumors or cancer [11].

Various healing approaches have been developed but the effects of cancer treatment have a negative impact on patients. Efforts to prevent and control cancer are being intensively carried out by the government, as for early detection and comprehensive management have been developed and aimed at people's risk. In the past decade, research on various prevention efforts is being carried out as focusing on better healing effectiveness. One of the focuses of our researchers is machine learning. The proposed method used is a hybrid convolutional neural network (CNN)-support vector machine (SVM) as many researchers have been applied separately. Some of the previous studies among these models are brain tumors using CNN [12], coronavirus disease 2019 using CNN [13], hepatitis using SVM [14], and Alzheimer using SVM [15]. The purpose of writing this research is to find out if machine learning technique can be used in the prevention and treatment of cancer. The results aim to prevent and control cancer with the detection of cancers' type before the unwanted side effects. This research contains of the backgrounds of cancer at first section, followed by data materials and methods in the second section, along with the proposed method in the third section, results and analysis in the fourth section, finally ends with discussion to conclusion.

## Materials and Methods

This section part explains the dataset used, along with the theoretical basis of hybrid CNN-SVM method and the evaluated model performance used.

### Data

X-rays are an electromagnetic waves radiation that produces pictures of your inside body parts in diverse shades of black and white [16]. This black and white image is produced because the body's tissues absorb different amounts of radiation, where X-ray examination aims to help doctors diagnose and monitor several body conditions as cancer [16]. The data materials used to perform in this research consist of X-ray computed tomography (CT) images taken from someone affected by cancer in 2019–2021 of time range, obtained from cancer imaging archive. A total observation of 900 X-ray CT images that were mixed between normal conditions and those who had cancer cells, which consists of 226, 241, 234, and 199 data for lung, liver, breast, and non-cancer images, respectively. Figure 1 is an example of the image data materials used in this research.

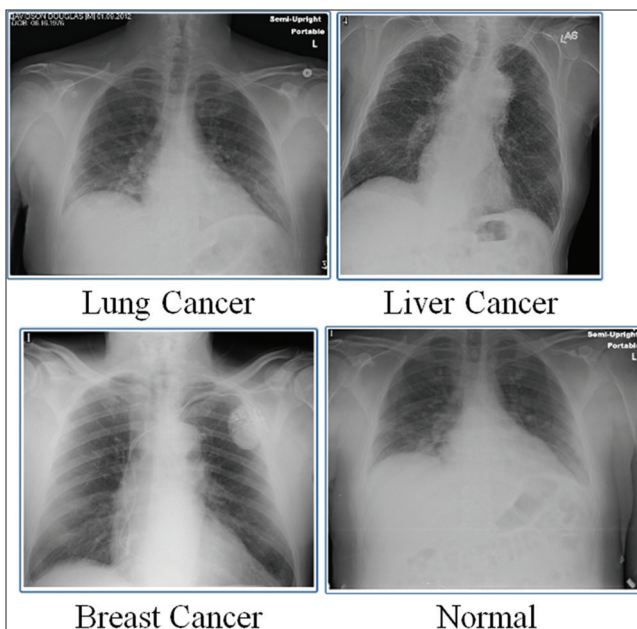


Figure 1: X-ray computed tomography image data materials used (Source: cancerimagingarchive.net)

### CNNs

CNNs as one of machine learning methods of deep neural networks is a cultivation of multilayer perceptron (MLP) which designed to produce or process data from two dimensions that have a network tier and many applications carried out in the image [17]. CNN consists of learning stage utilizing backpropagation and feedforward for classification. The working principle of CNN is one of the further developments of MLP with more dimensions [18], where each neuron of CNN is presented in two dimensions that not the same as MLP that only has one dimension. The data propagated into CNN are two dimensions data, therefore, the calculations are carried out linearly and using different weight parameters on CNN. Linear calculations in the CNN method use convolution calculations, with weights that are no longer just one dimension, but are already in the form of four dimensions which are a collection of various convolution kernels [19]. The following figure is an overview of the steps used in the process using the CNN method, as shown in Figure 2 [20].

Similar as neural networks, CNN has certain hidden layers of an input that has a single vector, where inside the input is a digital image that made to a single vector and inside the hidden layers is divers' neurons that have four mapping features [21]. This research used three main types of layers to build CNN Architectures of Convolutional, Pooling, and Fully Connected Layer. These layers will stack to form of Mobile Net V2 Architecture with SVM classification on output layer as the last layer which connected to previous hidden layer that presented into class classification, where SVMs method is used in this research.

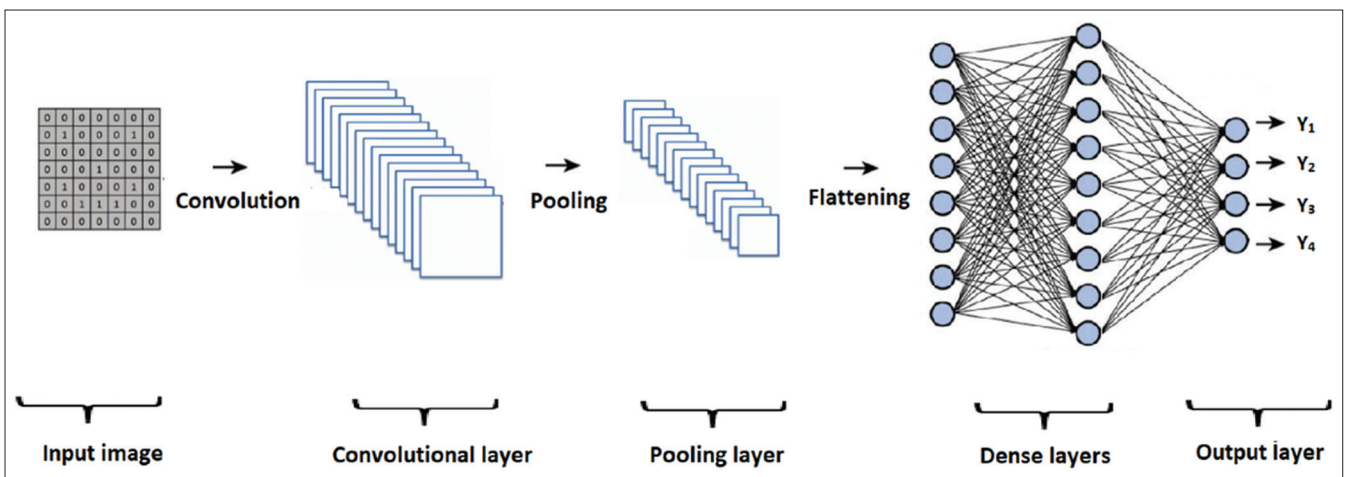


Figure 2: Convolutional neural networks architecture (Source: Applied Sciences Journal)

**SVMs**

SVMs are a hypothetical space in the form of linear functions feature that has high dimensions and trained algorithm based on optimization theory [22]. SVM performs a technique to find a separator function that can separate two data sets from two different classes. SVM was first introduced by Vapnik in 1992 as a series of several superior concepts in the field of pattern recognition when it was presented at the Annual Workshop on Computational Learning Theory [23]. This classification method is developed and applied as rooted in statistical learning theory whose results are promising to provide better results. Based on its characteristics, the SVM method is divided into two [24], linear SVM that separated linearly of two classes on the hyperplane with soft margins and non-linear SVM that applying kernel trick function to high-dimensional space. Figure 3 is an example of illustration of SVM method finds the best hyperplane [25].

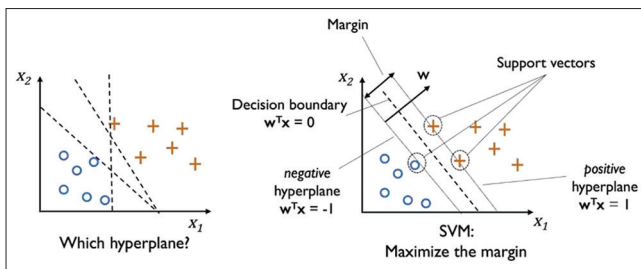


Figure 3: Support vector machines find the best hyperplane (Source: Python Machine Learning eBook)

The action of separating the two classes with a hyperplane is identified the right hyperplane, classifies the two classes, and then finds the hyperplane to separate to classes [26]. The hyperplane equation is shown in Equation (1) where  $w$  is the weight and  $b$  is the bias value.

$$w \cdot x + b = 0 \tag{1}$$

Using quadratic programming as its basic formulation as shown in Equation (2), with the constraints in Equation (3), Lagrange multiplier method also used as a technique in optimization problems with certain constraints as shown in Equation (4).

$$\min \left( \frac{1}{2} \|w\|^2 \right) \tag{2}$$

$$y_i (w \cdot x_i + b) \geq 1, \forall i = 1, \dots, N \tag{3}$$

$$L(w, b, \alpha) = \frac{1}{2} \|w\|^2 - \sum_{i=1}^N \alpha_i (y_i ((w \cdot x_i + b) - 1)), \quad i = 1, 2, \dots, N \tag{4}$$

Then, the values of  $w$  and  $b$  that obtained in Equations (5) and (6) are substituted to the function  $f(x)$  in Equation (7).

$$w = \sum_{i=1}^N \alpha_i y_i x_i \tag{5}$$

$$b = \frac{1}{N_S} \sum_{i \in S} \left( y_i - \sum_{j \in S} \alpha_j y_j x_j \right) \tag{6}$$

$$f(x) = \text{sign}(w \cdot x + b) \tag{7}$$

SVM regression as SVM for prediction is consisting of linear and nonlinear functions with primal and dual formulas [27], whose known as nonparametric technique because it relies on kernel functions. Generated by the transition process with SVM whose very dependent on the kernel function and the parameters used [27], types of kernels used in this research are Gaussian radial basis function (RBF) as described in Equation (8) below.

$$K(x_i, x_j) = \exp \left( -\frac{x_i - x_j^2}{\sigma^2} \right) \tag{8}$$

### Evaluated model performance

As one of the evaluated model performances, accuracy is a main parameter for observing the classification successes [28], where the greater the accuracy, then the better the classifier's performance. On determining the classifier, refers to the percentage of correct answers in the testing stage, confusion matrix is used for accurate measures, as shown in Table 1 [28].

**Table 1: Confusion matrix**

Actual	Prediction	
	Positive	Negative
Positive	$T_P$	$F_N$
Negative	$F_P$	$T_N$

Furthermore, the formula of accuracy, precision, and sensitivity as benchmark of the evaluated model performance is written in Equations (9), (10), and (11).

$$Accuracy = \frac{T_P + T_N}{T_P + T_N + F_P + F_N} \tag{9}$$

$$Precision = \frac{T_P}{T_P + F_P} \tag{10}$$

$$Sensitivity = \frac{T_P}{T_P + F_N} \tag{11}$$

Where:

- True positive ( $T_P$ ) is the number of samples suffering from cancer and correctly classified
- False positive ( $F_P$ ) is the number of non-cancer individuals misclassified as cancer
- False negative ( $F_N$ ) is the number of samples of patients with cancer and incorrectly classified
- True negative ( $T_N$ ) is the number of non-cancer individuals that correctly classified.

### The Proposed Method

The combining model of hybrid convolution neural network-SVM is applied to TensorFlow as a package framework that supports machine in the preparing of image data. The X-ray CT image data are classified into two classes, where the separation of image data using hold-out validation method that carried out in two parts with 10% up to 90% testing data. These different percentages were carried out to determine which testing data value of the model can use to maximize the classification. In convolutional part, binary cross-entropy and Adam (adaptive momentum) were used as the loss function and the optimizer of CNN model, respectively,

along with batch of 50 and 1000 epochs. Furthermore, for classification part, Gaussian RBF was used as the kernel function of SVM model with parameter gamma equals 5. The evaluated model performance was accuracy, precision, sensitivity, and running time. In addition, the proposed method flowchart was formed in Figure 4 and the summary of CNN architecture used on hybrid CNN-SVM is shown in Figure 5 as the number of layers, parameters, and output shape included.

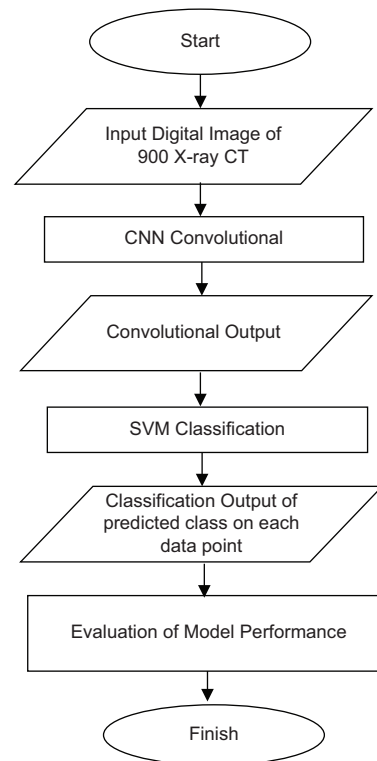


Figure 4: Flowchart of proposed method

Figure 4 shows the proposed method flowchart start with 900 X-ray CT images, with size of  $300 \times 300$  pixels that examined into CNN architecture in Figure 4. Forwarded to bunch of CNN layers, the output vector will divide into two datasets as training and testing using hold-out validation method. The model in this research used SVM, then validate the model with testing set. Finally, based on the predicted model, the predicted class of every data point will be evaluated so could determine the best model performance.

Figure 5 shows the summary of CNN architecture used on hybrid CNN-SVM with input values of  $n \times 300 \times 1$ . At the convolutional operation stage, four convolutional layers are used with first layer of  $32 - 3 \times 3$  filters as the value of 32 means the number of filters used in the  $3 \times 3$  matrices, followed by second layer of  $64 - 3 \times 3$  filters, third layer of  $96 - 3 \times 3$  filters, and fourth layer of  $128 - 3 \times 3$  filters. By reducing the size of feature map's or dimension obtained using pooling layers, this model used measurement  $2 \times 2$  of max pooling which was placed after all the convolutional layers. Due to the pooling layer's used, the largest value was obtained that create a new feature map. Using two strides, the filters on the layers of the previous matrix are shifts from left to right horizontally by two pixels before moving to the

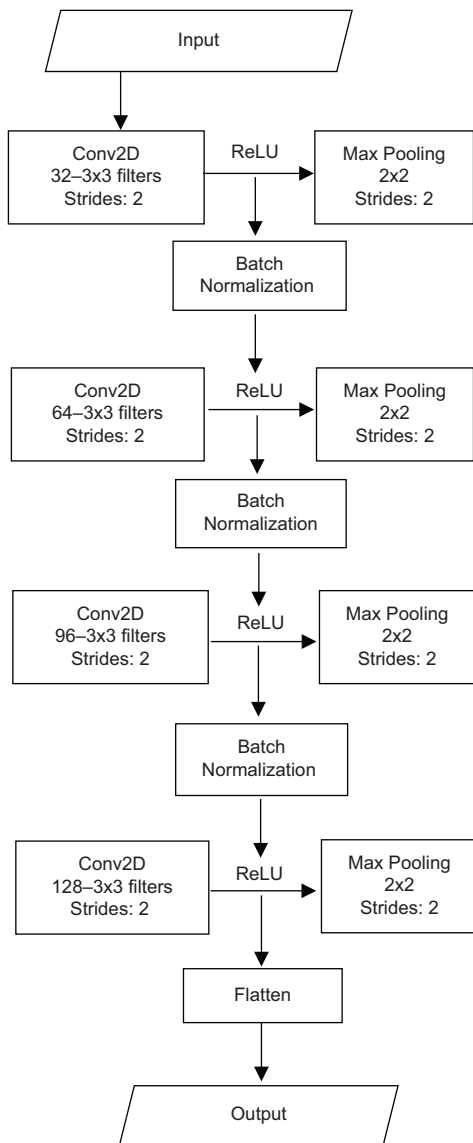


Figure 5: Summary of convolutional neural networks architecture

bottom leftmost vertically by two pixels. The result from most recent feature map was reconstructed by flattening where turning it into a one-dimensional array then finally the output.

## Results and Analysis

The proceeds of the proposed method execution of hybrid CNN-SVM on X-ray CT images dataset are presented. The model's performance is tested to determine the evaluation of accuracy, precision, and sensitivity of prediction model on every testing data proportion implemented based on confusion matrix, along with their running time. The total observation of 900 X-ray CT images that contain of mixture conditions among normal and cancer sufferers of lung, liver, also breast, the results of the model's performance of Hybrid CNN-SVM with kernel functions of Gaussian RBF equals 5 parameters of gamma are summarized in Tables 2-4.

Table 2 shows that the model's performance of hybrid CNN-SVM with dataset of lung cancer is a proper and competent model, with average of running time of  $\pm 0.6802$  s. At average of 86.95%, the highest

Table 2: Hybrid CNN-SVM model's performance on cancer of lung

Testing data (%)	Accuracy (%)	Precision (%)	Sensitivity (%)
10	99	98	99
20	100	99	100
30	98.03	98	98
40	98.52	98	99
50	89.41	88	98
60	99.01	99	99
70	99.15	99	99
80	91.04	89	100
90	95.42	95	98
Average	86.95	86.3	89

accuracy result is 100% at 20% testing data, with the lowest accuracy result of 89.41% at 50% testing data. Moreover, with average of 86.3%, the highest precision result is 99% at 20%, 60%, and 70% testing data, as the lowest is 88% at 50% testing data. Finally, for the sensitivity, with average of 89%, the highest and the lowest value resulted were 100% at 20% and 80% testing data and 98% at 30%, 50%, and 90% testing data, respectively.

Table 3: Hybrid CNN-SVM model's performance on cancer of liver

Testing data (%)	Accuracy (%)	Precision (%)	Sensitivity (%)
10	98.23	97	98
20	99.17	98	100
30	90.39	90	98
40	90.88	90	98
50	84.11	84	89
60	92.35	91	90
70	84.78	84	89
80	91.61	90	90
90	81.89	82	88
Average	81.34	80.6	84

Table 3 shows that the model's performance of hybrid CNN-SVM with dataset of liver cancer is a proper and competent model, with average of running time of  $\pm 0.7204$  s. At average of 91.34%, the highest accuracy result is 99.17% at 20% testing data, with the lowest accuracy result of 81.89% at 90% testing data. Moreover, with average of 80.6%, the highest precision result is 98% at 20% testing data, as the lowest is 82% at 90% testing data. Finally, for the sensitivity, with average of 84%, the highest and the lowest values resulted were 100% at 20% testing data and 88% at 90% testing data, respectively.

Table 4: Hybrid CNN-SVM model's performance on cancer of breast

Testing data (%)	Accuracy (%)	Precision (%)	Sensitivity (%)
10	96.47	96	100
20	98.35	99	100
30	97.39	99	100
40	95	95	98
50	94.11	94	98
60	94.5	95	98
70	92.26	92	90
80	92.79	93	90
90	91.89	92	89
Average	85.27	85.5	86.3

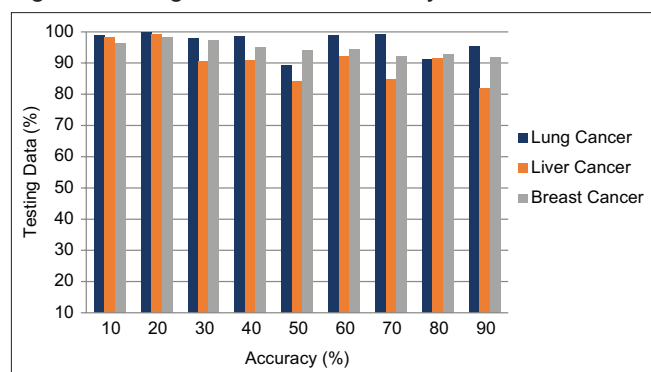
Table 4 shows that the model's performance of hybrid CNN-SVM with dataset of breast cancer is a proper and competent model, with average of running time of  $\pm 0.6853$  s. At average of 85.27%, the highest accuracy result is 98.35% at 20% testing data, with the

lowest accuracy result of 91.89% at 90% testing data. Moreover, with average of 85.5%, the highest precision result is 99% at 20% and 30% testing data, as the lowest is 92% at 90% testing data. Finally, for the sensitivity, with average of 86.3%, the highest and the lowest values resulted were 100% at 10%–30% testing data and 89% at 90% testing data, respectively. The authors also keep track of the comparison of accuracy generated between hybrid CNN-SVM programs in classifying all cancer data based on X-ray CT images. The comparison of hybrid CNN-SVM accuracy is shown in Table 5 and Figure 6.

**Table 5: Comparison of hybrid CNN-SVM accuracy's performance on cancer dataset**

Testing data (%)	Accuracy (%) of lung cancer	Accuracy (%) of liver cancer	Accuracy (%) of breast cancer	Average accuracy (%) of all cancer
10	99	98.23	96.47	97.9
20	100	99.17	98.35	99.17
30	98.03	90.39	97.39	95.27
40	98.52	90.88	95	94.8
50	89.41	84.11	94.11	89.21
60	99.01	92.35	94.5	95.28
70	99.15	84.78	92.26	92.06
80	91.04	91.61	92.79	91.81
90	95.42	81.89	91.89	89.73
Total average				86.2

Table 5 and Figure 6 show that the hybrid CNN-SVM accuracy results on all cancer dataset images are a feasible predict models, with average of running time that <10 s. The result of the highest accuracy value of hybrid CNN-SVM program trial is 100% on 20% testing data of lung cancer followed by 99.17% on 20% testing data of liver cancer and 98.35% on 20% testing data of breast cancer. Furthermore, based on the trials model's program, with total average of 86.2%, the highest average accuracy value for all the cancer dataset images is 99.17% on 20% proportion of the testing data. As being shown, hybrid CNN-SVM is a proper and feasible model with competence of total highest average of 99.17% accuracy value.



**Figure 6: Graph of hybrid convolutional neural networks-support vector machines accuracy's performance on cancer dataset**

## Discussion and Conclusion

The writing research of aim to support health sector as prevent and focusing on better effectiveness of diagnose cancer diseases is adequately and

strategically good proposed. The proposed method used of hybrid CNN-SVM and data materials from a search on the site cancerimagingarchive.net that obtained total of 900 data in the 2019–2021 of time range was correctly predict the data. The analysis is carried out using the proposed method by reviewing, identifying, and presenting it as the results obtained that machine learning has an influence on the classification of cancer. Based on the trials model's program, the highest accuracy value of hybrid CNN-SVM is 100% on 20% testing data of lung cancer followed with 99.17% on 20% testing data of liver cancer and 98.35% on 20% testing data of breast cancer. In addition, with total average of 86.2%, the highest average accuracy value for all the cancer dataset images is 99.17% on 20% proportion of the testing data. Thereof, the combining model of hybrid CNN-SVM has the best performance with 99.17% accuracy value. The proposed method can detect cancer cells with an effective mechanism of action so can has the potential to inhibit in the future researches with more extensive data materials and various ailments.

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