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Kushner-Stratonovich Dice Segmented Curvelet (KSDSC) deep convolutional neural learning for heart disease prediction

Damodharan D
Research scholar &Assistant Professor, Galgotias University, Greater Noida, India
Corresponding author email: damodharan@galgotiasuniversity.edu.in

Amit Kumar Goel
Professor, Galgotias University, Greater Noida, India
Email: amit.goel@galgotiasuniversity.edu.in

***Abstract*---**Data mining is commonly used method for processing large amount of data in heart disease prediction. Many heart disease prediction researches are carried out by different authors. But the accuracy level was not improved. In order to address these issues, Kushner-Stratonovich Dice Segmented Haar Wavelet (KSDSC) Deep Convolutional Neural Learning Model is introduced. The main aim of KSDSC Model is to perform efficient heart disease prediction with five layers, namely one input layer, three hidden layers and one output layer. Initially, ultrasound images are collected as an input at input layer. An image pre-processing is carried out using Kushner-Stratonovich Filter to eliminate the noisy pixels from US image and transmitted to hidden layer 2. Sørensen–Dice Image Segmentation Process partitions the preprocessed image into number of divisions in hidden layer 2. After that in hidden layer 3, the multiple features are extracted using Curvelet transform from segmented image and sent to the output layer. The output layer uses softmax yolov4 darknet53 activation function to match extracted features for heart disease prediction. Experimental analysis is performed on parameters such as prediction accuracy, false positive rate, and prediction time with respect to a number of US images. The qualitative and quantitative results illustrate our proposed KSDSC Model attains better results than the existing methods.

***Keywords*---**Heart disease, Image pre-processing, ultrasound images, Sørensen–Dice, Kushner-Stratonovich Filter.

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1 Introduction

Heart disease is considered as the significant cause of mortality among the world population. Heart disease prediction is considered as an essential problem in clinical data analysis. The hybrid meta-heuristic search termed Jaya Algorithm with Red Deer Algorithm (J-RDA) was employed in [1] for optimized feature extraction. After feature optimization, the hybrid clustering was carried out for heart disease prediction. But, prediction time consumption was not reduced by J-RDA. A combined reinforcement multitask progressive time-series networks (CRMPTN) model was introduced in [2] to predict the grade of coronary heart disease. But, the prediction accuracy was not improved.

A PSO merged LA update (PM-LU) algorithm was designed in [3] to solve the heart disease prediction issues with dimensionally reduced features. Machine learning (ML) was employed to reduce the symptoms consistent with heart disease. A dimensionality reduction method was employed in [4] for identifying the heart disease features by feature selection method. However, the computational cost was not reduced by ML.

A feature selection algorithm termed Information Gain based Feature Selection (IGFS) was introduced in [5] to increase the ML approach performance. IGFS mechanism was employed to perform relevant feature identification for class label determination. But, the feature selection accuracy was not increased by IGFS. A new framework was introduced in [6] for heart disease prediction. However, time complexity was not reduced.

A two stage method was introduced in [7] to predict the heart disease. The first stage included sparse autoencoder (SAE) to study the best representation. A convolutional neural network-differential evolution algorithm (CNN-jSO) approach was designed in [8] for heart (cardiac) disease prediction. A LASSO based feature weight assessment was carried out in [9] for majority-voting identification. But, prediction time was not reduced by LASSO. A new ensemble method was introduced in [10] for heart disease prediction. But, the accuracy was not increased. The aim of KSDSC Model is given as:

- The key aim of KSDSC Model is to perform efficient heart disease prediction.
- An ultrasound images are considered as an input and image pre-processing is carried out in KSDSC Model using Kushner-Stratonovich Filter to eliminate the noise pixels from US image.
- Sørensen–Dice Image Segmentation Process in KSDSC Model divides the preprocessed image into segments and features are extracted using curvelet transform in KSDSC Model.
- The output layer used softmax yolov4 darknet53 activation function in KSDSC Model to match extracted features for heart disease prediction.

The paper is structured as. In Section 2, the related works of heart disease prediction are reviewed. Section 3 provides a brief description of KSDSC Model. In section 4, the simulation settings are specified with certain parameters. The simulation results of proposed KSDSC Model with the existing methods are discussed in Section 5. The conclusion is given in section 6.

2 Related Works

An individual with heart disease risk gets predicted in [11] by using applying machine learning algorithms on training data. But, the accuracy during prediction was not improved by CNN algorithm. An efficient intelligent medical system was introduced in [12] for identifying the patient heart condition to perform accurate cardiovascular diseases diagnosis. But, the time consumption was not reduced by intelligent medical system.

An intelligent computational predictive system was designed in [13] for cardiac disease identification and diagnosis. A heart disease prediction algorithm was introduced in [14] with feature selection method and deep neural networks. Ensemble learning technique was introduced in [15] to improve the heart disease performance. A smart healthcare system was introduced in [16] for heart disease prediction. However, time complexity was not reduced by smart healthcare system.

A heart disease prediction system was introduced in [17] for guessing heart disease risk level. The risk factors causing heart disease was considered in [18]. However, the time complexity was not reduced by designed algorithm. MLP-EBMDA was introduced in [19] for heart disease classification. The heart disease data was collected and pre-processed. The relevant features were chosen through optimized unsupervised technique. But, the computational complexity was not minimized by MLP-EBMDA. An improved k-means neighbor classification was introduced in [20] to perform efficient heart diseases prediction. But, the computational cost was not reduced.

3 Methodology

Heart disease has received large attention in the medical research. The heart disease diagnosis is a difficult task to present the automated prediction about heart condition of patient for further treatment. Many researchers performed their research on heart disease prediction techniques. Therefore, Kushner-Stratonovich Dice Segmented Haar Wavelet (KSDSC) Deep Convolutional Neural Learning Model is introduced to perform an efficient heart disease prediction with lesser time consumption. The structural diagram of KSDSC Model is illustrated in figure 1.

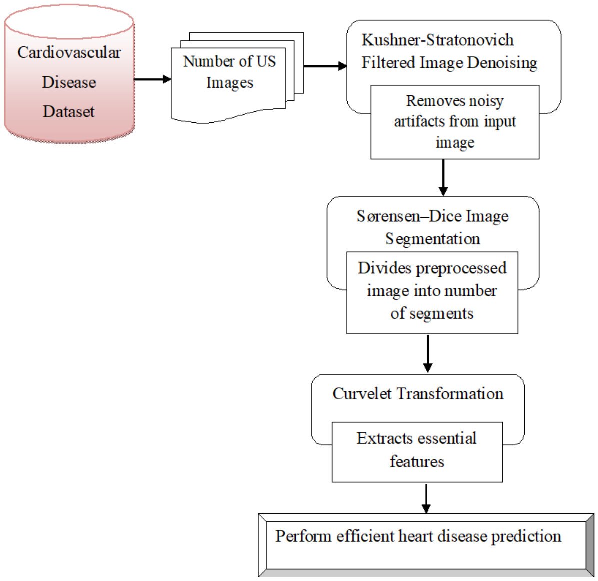

Figure 1. *Architecture of proposed KSDSC Model*

Figure 1 illustrates the process diagram of proposed KSDSC Model to attain heart disease prediction. The input US images $USI_1, USI_2, USI_3 \ldots\ldots USI_m$are gathered from the database. The collected US images are used to the deep convolutional learning technique. The kushner-stratonovich filtered preprocessing increases the image quality through removing the noisy pixels. Secondly, the sørensen–dice image segmentation partitioned the pre-processed image into segments. Thirdly, the features are extracted for accurate classification to perform heart disease prediction.

Kushner-Stratonovich Dice Segmented Curvelet (KSDSC) Deep Convolutional Neural Learning

A Deep Convolutional Neural Network (DCNN) is used for processing the structured data arrays like images. Convolutional deep neural networks used in computer vision for visual applications like image classification. The designed DCNN comprised six layers for performing efficient heat disease prediction. The input layer collects the number of US images '$USI_1, USI_2, USI_3, \ldots USI_n$'. The input layer '$I(t)$' is formulated as,

$$I(t) = bias + [\sum_{i=1}^{n} USI_i * \omega e_{in}] \quad [1]$$

From (1), 'USI_i'’represent the ultra sound images. Bias value is considered as '1'. 'ωe_{in}' in denote the weight value at input layer. Then, the input is transmitted to the hidden layer 1 where image pre-processing is carried out. Kushner-Stratonovich Filtered Image Denoising is performed to reduce the noise of ultra sound images for image quality enhancement. Kushner-Stratonovich Filtered Image Denoising '$KSFID(x)$' is used to eliminate the noise drawn based on conditional probability density of stochastic non-linear dynamic system.KSFIDis formulated as,

$$KSFID(x) = \sum_{i=1}^{n} USI_i h(x,t)dt \qquad [2]$$

From (2), '$KSFID(x)$' denotes the denoised image. '$h(x,t)$' denotes the conditional probability density function. Then, the denoised image is sent to the hidden layer 2. Sørensen–Dice Image Segmentation Process partitions the denoised image into different parts based on their features.

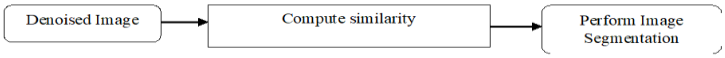

Figure 2. *Sørensen–Dice Image Segmentation*

Figure 2 describes the Sorensen dice similarity function taken with input denoised image. Sørensen–Dice Similarity Index computes correlation between the pixels. It is computed as,

$$SDSI = \frac{2|Pixel_x \cap Pixel_y|}{|Pixel_x| + |Pixel_y|} \qquad [3]$$

From (3), '$SDSI$' symbolizes the sørensen–dicesimilarity index. '$Pixel_x$' denotes the image pixels. '$Pixel_y$' denotes the neighboring pixel of denoised image. The similarity value ranges between 0 and 1. The pixels are partitioned into many regions in KSDSC Model. After that, the segmented image is sent to the hidden layer 4. In that layer, feature extraction is carried out by using curvelet transformation. Curvelet Transformation presents the global data analysis at many resolutions. The lower resolutions provide the information about global features of US image extracted and the higher resolutions gives the local features of US image. Curvelet Transformation attains the sub-bands of US image with different resolution levels. Curvelet transform is a transformation technique with multiresolution analysis. Curvelet transform includes the directional parameters with needle-shaped elements and high directional specificity. Curvelet coefficients are obtained from scaling and windowing function. Window frame width 'W' and length 'L' is selected by,

$$Width = Length^2 \qquad [4]$$

From (4), it is termed as curvelet scaling law. The sub-band decomposition of US image is carried out by,

$$p_b \to (P_{lf}p, \Delta_1 p, \Delta_2 p, ..)$$

[5]

From (5), 'p_b' represent the pixel bands. 'P_{lf}' represents low pass filter, 'Δ_1' and 'Δ_2' denotes the high pass filter. By this way, image features are extracted. The output of hidden layer is,

$$Hidden(t) = \sum_{i=1}^{n} USI_i * \omega_{in} + [Hidden(t-1) * \omega_{hh}] \quad [6]$$

From (6), '$Hidden(t)$' denote hidden layer output. 'ω_{in}' symbolizes the weight between input and hidden layers. '$Hidden(t-1)$' symbolize previous hidden layer result. Then, the hidden layer result is sent to output layer. In that layer, the classification is performed through softmax yolov4 darknet53 activation function to analyze the features for heart disease prediction.

$$Softmax_{fun} = \frac{e^{x_i}}{\sum_{j=1}^{K} 1+e^{x_i}} \quad [7]$$

From (7), '$Softmax_{fun}$' symbolizes the softmax yolov4 darknet53 activation function. 'x_i' symbolize the training segmented image. The output layer of KSDSC Model is denoted as,

$$Output(t) = \omega_{oh} * Hidden(t) \quad [8]$$

From (8), '$Output(t)$' denotes the output layer result. 'ω_{oh}' symbolizes the weight between hidden layer and output layer. The steps of Kushner-Stratonovich Dice Segmented Curvelet (KSDSC) Deep Convolutional Neural Learning is described as,

Algorithm 1: Kushner-Stratonovich Dice Segmented Curvelet (KSDSC) Deep Convolutional Neural Learning
Input: Database, Ultra Sound Image $USI_2, USI_3 \ldots . USI_n$
Begin 1: Initialize number of ultra sound images$USI_2, USI_3 \ldots . USI_n$ 2: for each US image 3: Eliminates the noisy pixels through preprocessing 4: Partition the images through sørensen–dice similarity function 5: Measure the similarity between pixels 6: Extract feature using curvelet transformation 7: Apply softmax yolov4 darknet53 activation function for extracted features 8: if ($Softmax_{fun} > th$)then 9: Image is abnormal 10: Else 11: Image is normal 12: End if 13: End for End

Algorithm 1 presents the process of heart disease prediction in KSDSC Model. US images are considered as an input. The preprocessing, image segmentation feature extraction and classification are performed. Finally, the heart disease prediction is performed with lesser time complexity.

4 Database Explanation

The proposed KSDSC Model and the existing Jaya Algorithm with Red Deer Algorithm (J-RDA) [1] and existing combined reinforcement multitask progressive time-series networks (CRMPTN) model is implemented with help of Python programming for heart disease prediction as normal or abnormal. Many US Images are gathered from CETUS database. The URL of input database is http://humanheart-project.creatis.insa-lyon.fr/database/.The input US image is preprocessed to eliminate the noisy artifacts and attain the quality improved US images. Then, the input preprocessed images are segmented. The texture, color, shape, intensity features are extracted from segmented images. At last, classification is performed with help of the extracted features for performing the heart disease prediction

5 Results and Discussion

The proposed KSDSC Model and the existing J-RDA [1] and existing CRMPTN model [2] are evaluated through prediction accuracy, false positive rate and prediction time.

5.1 Prediction Accuracy:

Prediction accuracy is ratio of number of US images that are correctly identified as diseased image or normal image through segmentation and classification process from given input US images. It is calculated as

$$Pre_{Acc} = \left(\frac{Number of images correctly predicted}{Number\ of\ US\ images}\right) * 100 \qquad [9]$$

From (9), 'Pre_{Acc}' symbolize the prediction accuracy. The prediction accuracy is determined in percentage (%).

Table 1
Tabulation of Prediction Accuracy

Number of US Images (Number)	Prediction Accuracy (%)		
	J-RDA	CRMPTN model	KSDSC Model
50	45	60	64
100	47	65	68
150	52	68	69
200	53	69	70
250	55	72	71
300	59	73	75
350	61	75	77
400	63	77	78
450	66	76	82
500	68	74	83
550	71	79	85
600	72	80	87
650	74	87	90
700	76	85	93
750	78	84	90

800	80	87	92
850	83	89	93
900	85	85	94
950	88	89	95
1000	89	92	98

Table 1 describes the experimental results of prediction accuracy for different US image varies from 50 to 1000. The attained results of prediction accuracy using KSDSC Model are compared to the two conventional methods namely the J-RDA [1] and CRMPTN model [2]. The proposed KSDSC Model efficiently achieves higher prediction accuracy than existing methods. Let us consider that number of US images for conducting experiments. By using KSDSC Model, the observed prediction accuracy is 98% while the prediction accuracy of the conventional methods [1] and [2] are 89% and 92% correspondingly. The various prediction accuracy results are achieved for every technique. The graphical representation of prediction accuracy is illustrated in figure 3.

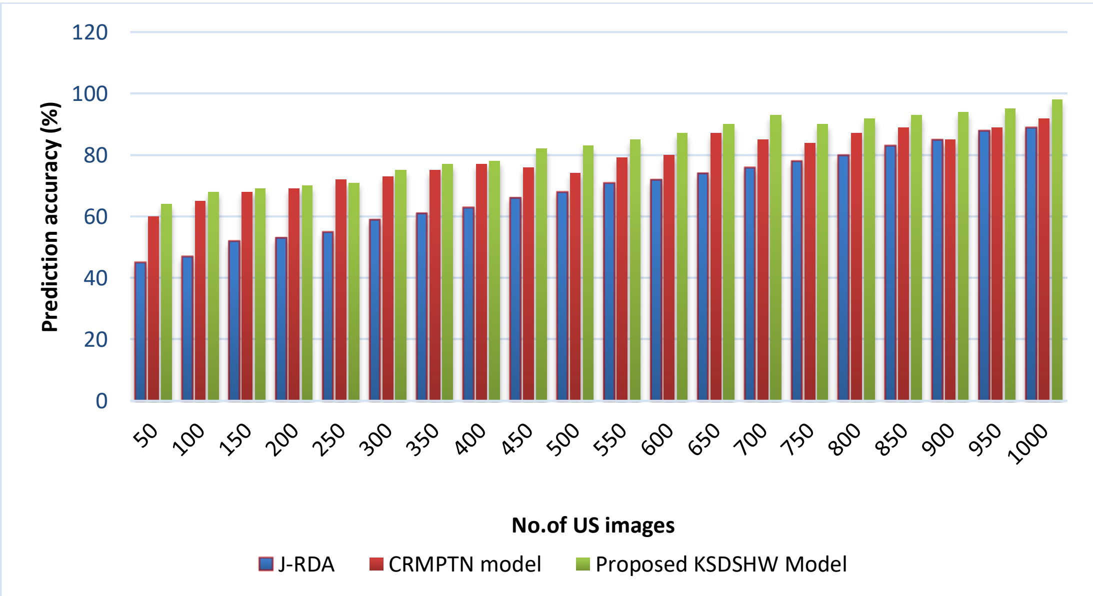

Figure 3. *Measurement of Prediction Accuracy*

Figure 3 illustrates prediction accuracy results. The number of US Images is considered in the horizontal axis as well as prediction accuracy is attained at vertical axis. The green color column denotes the prediction accuracy of KSDSC Model whereas blue color and red color represents the prediction accuracy of J-RDA [1] and CRMPTN model [2]. The prediction accuracy of proposed KSDSC Model is higher than existing methods. This is due to the application of deep convolutional neural classifier in KSDSC Model. The kushner-stratonovich filtered preprocessing improves the image quality through eliminating the noise pixels. The sørensen–dice image segmentation divided the pre-processed image into number of partitions. Then, the features are extracted to perform accurate classification for heart disease prediction with higher accuracy. Finally, proposed

KSDSC Model enhances the prediction accuracy by 9% compared to J-RDA [1] and 6% compared to CRMPTN model [2] correspondingly.

5.2 Analysis on False positive rate:

False positive rate is computed as the ratio of number of US images that are inaccurately predicted as diseased US image or normal image through performing segmentation and classification process from given input US images. It is calculated as,

$$FP_{Rate} = \left(\frac{Number of images incorrectly\ predicted}{Number\ of\ US\ images}\right) * 100 \qquad [10]$$

From (10), 'FP_{Rate}symbolizes thefalse positive rate. The false positive rate is measured in percentage (%).

Table 2
Tabulation of False positive rate

Number of US Images (Number)	False positive rate (%) J-RDA	CRMPTN model	KSDSC Model
50	80	60	35
100	76	58	41
150	73	55	43
200	69	51	38
250	65	48	36
300	62	43	33
350	59	40	29
400	55	37	26
450	50	36	23
500	46	33	20
550	43	30	19
600	40	29	15
650	39	27	13
700	36	25	11
750	31	24	10
800	29	21	8
850	26	19	7
900	22	15	6
950	21	13	5
1000	18	10	2

Table 2 explains the experimental results of false positive rate for 50 to 1000 US images. The achieved results of false positive rate using KSDSC Model are compared to two existing techniques namely the J-RDA [1] and CRMPTN model [2]. The proposed KSDSC Model efficiently attains lesser false positive rate than existing methods. Let us consider that number of US images for experimental consideration. By using KSDSC Model, the observed false positive rate is 30% while the false positive rate of the conventional methods [1] and [2] are 15% and

10% respectively. The different false positive rate results are attained for every method. The graphical illustration of false positive rate is illustrated in figure 4.

Figure 4 describes the results of false positive rate along with number of US images varying from 50 to 1000. The number of US Images is taken in horizontal direction and the false positive rate is considered in the vertical axis. The green color column denotes the false positive rate of KSDSC Model whereas blue color and red color symbolizes the false positive rate of J-RDA [1] and CRMPTN model [2]. The false positive rate of proposed KSDSC Model is lesser than conventional methods. This is because of using the deep convolutional neural classifier in proposed KSDSC Model. The kushner-stratonovich filtered preprocessing eliminates the noisy pixels to enhance the image quality.

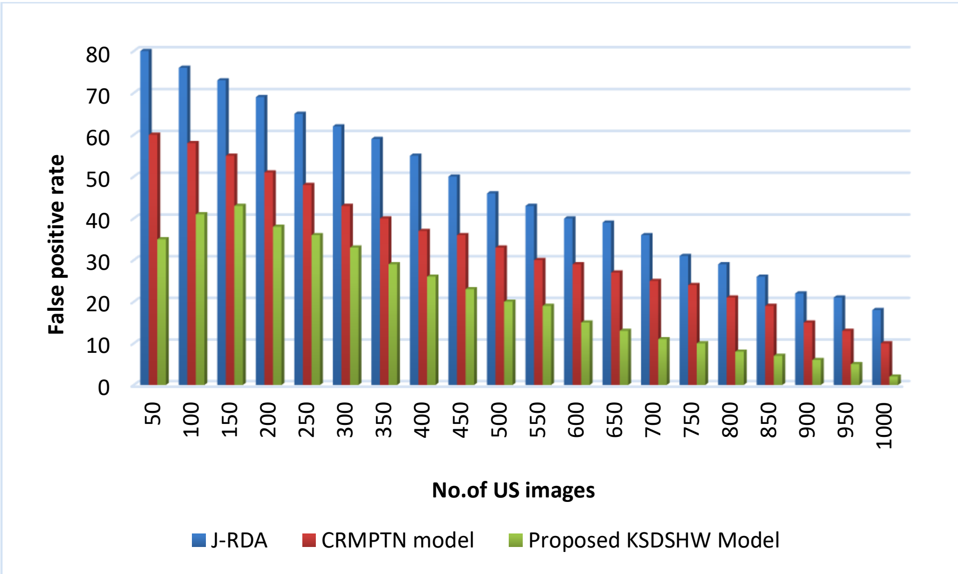

Figure 4. *Measurement of False positive rate*

The sørensen–dice image segmentation partitions the image into number of segments and features are extracted for heart disease prediction with lesser false positive rate. As a result, proposed KSDSC Model reduces the false positive rate by 70% when compared to J-RDA [1] and 52% when compared to CRMPTN model [2] correspondingly.

5.3 Analysis on Prediction Time:

Prediction time is amount of time consumed to predict the heart disease from given input US images through pre-processing, segmentation and classification task. The prediction time is calculated as,

$$Pre_{\ Time} = Number\ of\ MRI\ images * t(PSI) \qquad [11]$$

From (11), '$Pre_{\ Time}$' symbolizes the prediction time. '$t(PSI)$' denote the consumed for predicting single US image. It is computed in terms of milliseconds (ms).

Table 3
Tabulation of Prediction Time

Number of US Images (Number)	Prediction Time (ms) J-RDA	CRMPTN model	KSDSC Model
50	25	21	15
100	27	23	18
150	29	25	19
200	30	26	21
250	31	28	23
300	33	31	25
350	35	33	28
400	37	36	29
450	39	37	31
500	41	39	33
550	43	40	35
600	45	42	37
650	46	44	38
700	49	47	40
750	51	48	41
800	53	51	43
850	55	52	46
900	58	55	48
950	61	56	51
1000	64	58	53

Table 3illustrates the experimental results of prediction time for 50 to 1000 US images from input dataset. The results of prediction time using KSDSC Model are compared to two conventional techniques namely the J-RDA [1] and CRMPTN model [2]. The proposed KSDSC Model efficiently attained lesser prediction time than existing methods. Let us consider that number of US images is 40for experimental consideration. By using KSDSC Model, the observed prediction time is 32ms while the prediction time of the traditional methods [1] and [2] are 48ms and 42ms respectively. The different prediction time results are achieved for each technique. The graphical representation of prediction time is illustrated in figure 5.

Figure 5 illustrates prediction time result along with number of US images ranging from 50 to 1000. The green color column symbolizes the prediction time of KSDSC Model whereas blue color and red color denotes the prediction time of J-RDA [1] and CRMPTN model [2]. The prediction time of proposed KSDSC Model is lesser than traditional techniques. This is because of deep convolutional neural classifier application in proposed KSDSC Model.

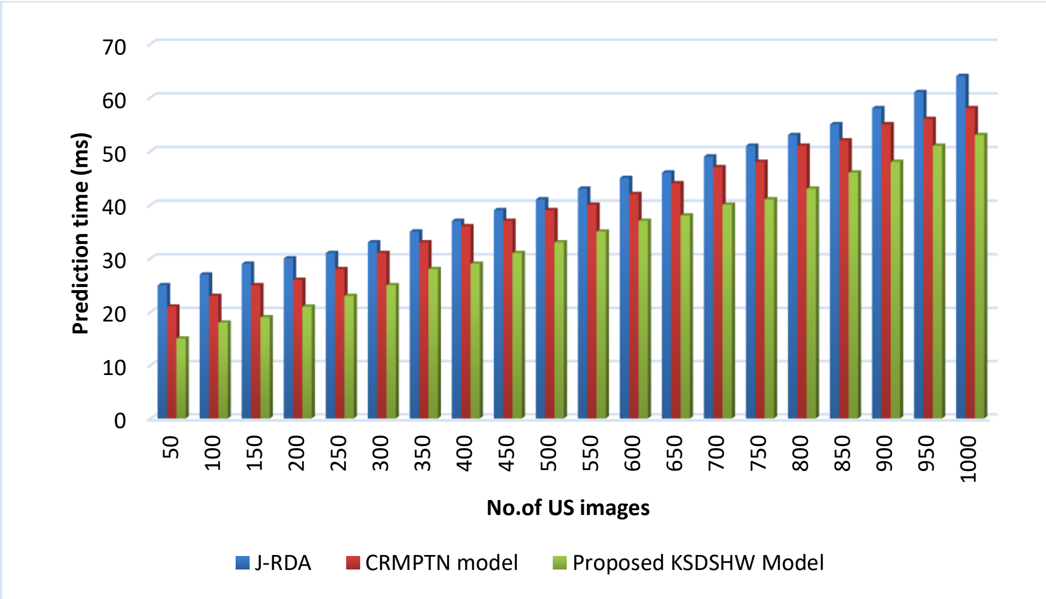

Figure 5. *Measurement of Prediction Time*

In the designed model, kushner-stratonovich filtered preprocessing eliminates the noisy pixels to improve the image quality. Then, sørensen–dice image segmentation divides the pre-processed image into different segments. The features are extracted from segmented image for performing the heart disease prediction with lesser time consumption. Therefore, proposed KSDSC Model reduces the prediction time by38% when compared to J-RDA [1] and 24% when compared to CRMPTN model [2] correspondingly.

6 Conclusion

A heart disease prediction model called KSDSC Model is introduced. Kushner-Stratonovich Filter eliminates the noisy pixel from US image to improve image quality. Sørensen–Dice Image Segmentation Process segments the preprocessed image and features are extracted using curvelet transformation. The softmax yolov4 darknet53 activation function matches the extracted features for performing the heart disease prediction. The experimental analysis is carried out with help of heart disease prediction dataset. The qualitative and quantitative results discussion shows that the KSDSC Model has received better performance when compared to traditional methods.

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