Classifying shoulder implants in X-ray images using Big data techniques

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Abstract. This research work focuses on optimal solution for the image detection and segmentation. The prosthesis may – a few or numerous years after it was embedded – come needing fix or substitution. In a portion of these cases, the maker and the model of the prosthesis might be obscure to the patients and their essential consideration specialists, for instance when the medical procedure was led in another nation where the patient has presently no admittance to the records. The highest accuracy value is 81.68% which is while applying the=7k=6 and the lowest accuracy value is 65.6% when apply the k=7. The highest precision value is 81.68% while applying the k=1 and very lowest precision value is 73.69% lies on k=2 and k=9.The highest recall value is 83.69% which is produced by while applying the parameter k=6, the lowest recall value is 65.76% while applying the parameter k=9. The K=10 model takes more time to build the model is while applying the k=10 and very low time consumption model is k=8. Another conceivable instance of not knowing the specific producer and model could be expected uncertainty in clinical records or clinical images.

Keywords: KNN, Instance based classifier, Lazy classifier, TSA,UW.

1 Introduction

Total Shoulder Arthroplasty (TSA) is a typical intrusive system for treating harmed shoulder joints, where the shoulder ball is supplanted with a prosthesis.[1] The method is gone before and followed by a progression of X-beam pictures to evaluate arrangement and fit.[2] Common explanations behind going through TSA medical procedure are basic shoulder wounds or serious arthritis.[3,17] The technique mitigates torment and reestablishes movement to the patients shoulder.[4,16] There are a few distinct makers delivering prostheses, and every one of them offers a few unique models to all the more likely fit any sort of circumstance and patient.[5,15]The prosthesis may – a few or numerous years after it was embedded – come needing fix or replacement.[6,14] In a portion of these cases, the producer and the model of the prosthesis might be obscure to the patients and their essential consideration specialists, for instance when the medical procedure was directed in another nation where the patient has right now no admittance to the records.[7,13] Another conceivable instance of not knowing the specific maker and model could be expected uncertainty in clinical records or clinical images.[8,12] right now, the errand of recognizing a prosthesis model in such cases is based on thorough assessments and visual correlations of X-

beam pictures taken from the embed by clinical experts.[9,10,11] This can be a dreary assignment and requires time and exertion for each new patient.

In this paper presents in section 2 presents the materials and methods adopted and section 3 presents the details of the experiments and discussions. Finally section 4 concludes the paper by sharing our inferences and future plans.

2 Materials And Methods

The dataset gathered from UCI vault. Pictures were gathered by Maya Stark at BIDAL Lab at SFSU for her MS postulation project. They are from The UW Shoulder Site ([Web Link]), producer sites, and Feeley Lab at UCSF. The first assortment included 605 X-beam pictures. Eight pictures that seemed to have been taken from similar patients were eliminated, bringing about the last 597 pictures. The last set contains pictures from the accompanying makers: 83 from Cofield, 294 from Depuy, 71 from Tornier, and 149 from Zimmer, bringing about a 4-class arrangement issue. Class marks are given as the maker name in document names. Pictures are with 8-bit grayscale and different measurements in jpeg design. Weka 3.9.8.tool has implemented for the analysis and the below methods have implemented in this research work.

- Instance based classifier(KNN)

3 Results And Discussions

In this section focuses on the results and discussions of the instance based classifier implemented in this dataset.

Table 1: Instance based classifier Vs Accuracy

S.No	K	Accuracy
1	1	79.49
2	2	79.44
3	3	74.81
4	4	77.43
5	5	73.69
6	6	81.68
7	7	65.6
8	8	76.19
9	9	77.43
10	10	73.69

The above table clearly shows that the instance based classifier is producing the accuracy levels are different while doing the parameter tuning like K parameter. In this dataset we implemented the lazy classifier while K=1 then the system gets an accuracy value is 79.49%, while K=2 then the system gets an accuracy value is 79.44%, while K=3 then the system gets

an accuracy value is 74.81%, while K=4 then the system gets an accuracy value is 77.43%, while K=5 then the system gets an accuracy value is 73.69%, while K=6 then the system gets an accuracy value is 81.68%, while K=7 then the system gets an accuracy value is 65.6%, while K=8 then the system gets an accuracy value is 76.19%, while K=9 then the system gets an accuracy value is 77.43%, while K=10 then the system gets an accuracy value is 73.69%.
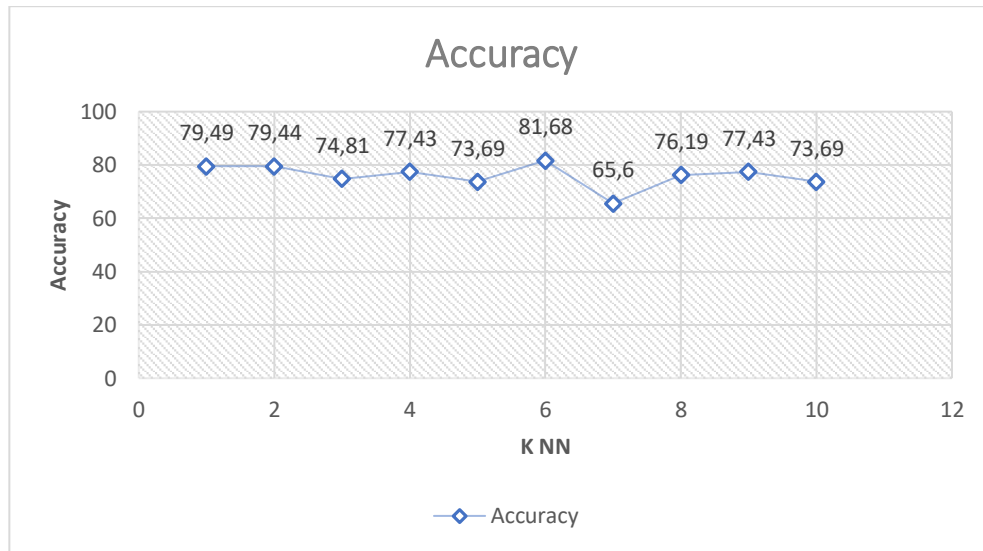

Figure 1: Instance based classifier Vs Accuracy

The above diagram shows that the highest accuracy value is 81.68% which is while applying the=7k=6 and the lowest accuracy value is 65.6% when apply the k=7

Table 1: Instance based classifier Vs Precision

S.No	K	Precision
1	1	81.68
2	2	73.69
3	3	78.14
4	4	79.32
5	5	79.49
6	6	80.44
7	7	74.81
8	8	77.43
9	9	73.69
10	10	74.81

The above table clearly shows that the instance based classifier is producing the precision value levels are different while doing the parameter tuning like K parameter. In this dataset we implemented the lazy classifier while K=1 then the system gets a precision value is 81.68%, while K=2 then the system gets a precision value is 73.69%, while K=3 then the system gets a precision value is 78.14%, while K=4 then the system gets a precision value is 79.32%, while

K=5 then the system gets a precision value is 79.49%, while K=6 then the system gets a precision value is 80.44%, while K=7 then the system gets a precision value is 74.81%, while K=8 then the system gets a precision value is 77.43%, while K=9 then the system gets a precision value is 73.69%, while K=10 then the system gets a precision value is 74.81%.

Precision

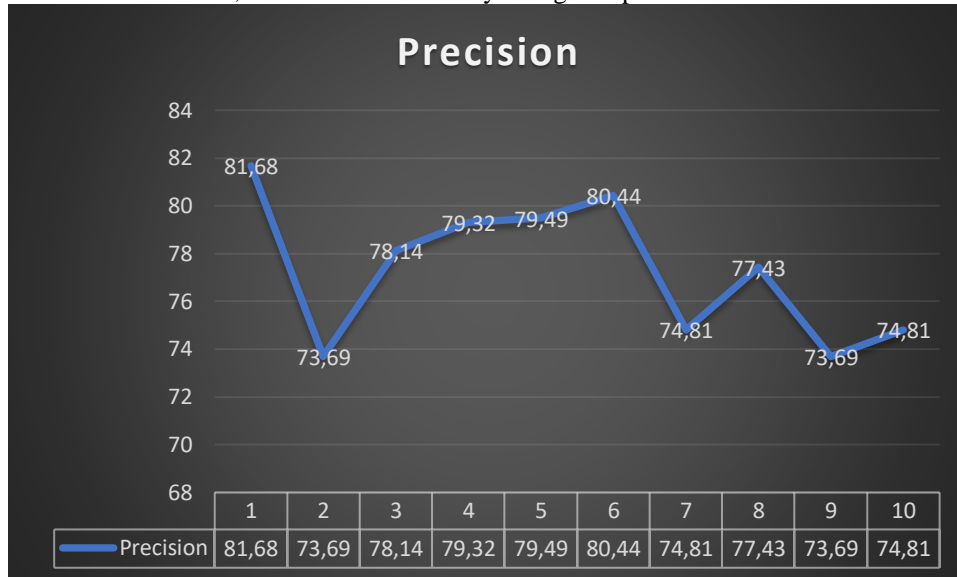|	1	2	3	4	5	6	7	8	9	10
Precision	81,68	73,69	78,14	79,32	79,49	80,44	74,81	77,43	73,69	74,81

Figure 2: Instance based classifier Vs Precision

The above diagram clearly shows that the highest precision value is 81.68% while applying the k=1 and very lowest precision value is 73.69% lies on k=2 and k=9.

Table 2: Instance based classifier Vs Recall

S.No	K	Recall
1	1	79.43
2	2	71.69
3	3	80.68
4	4	75.6
5	5	75.19
6	6	83.69
7	7	74.81
8	8	81.68
9	9	65.76
10	10	75.89

The above table 2 clearly shows that the instance based classifier is producing the recall value levels are different while doing the parameter tuning like K parameter. In this dataset we implemented the lazy classifier while K=1 then the system gets a recall value is 79.43%, while K=2 then the system gets a recall value is 71.69%, while K=3 then the system gets a recall value is 80.68%, while K=4 then the system gets a recall value is 75.6%, while K=5 then the system gets a recall value is 75.19%, while K=6 then the system gets a recall value is 83.69%,

while K=7 then the system gets a recall value is 74.81%, while K=8 then the system gets a recall value is 81.68%, while K=9 then the system gets a recall value is 65.76%, while K=10 then the system gets a recall value is 75.89%.

Recall

	K	Recall
Ряд1	1	79,43
Ряд2	2	71,69
Ряд3	3	80,68
Ряд4	4	75,6
Ряд5	5	75,19
Ряд6	6	83,69
Ряд7	7	74,81
Ряд8	8	81,68
Ряд9	9	65,76
Ряд10	10	75,89

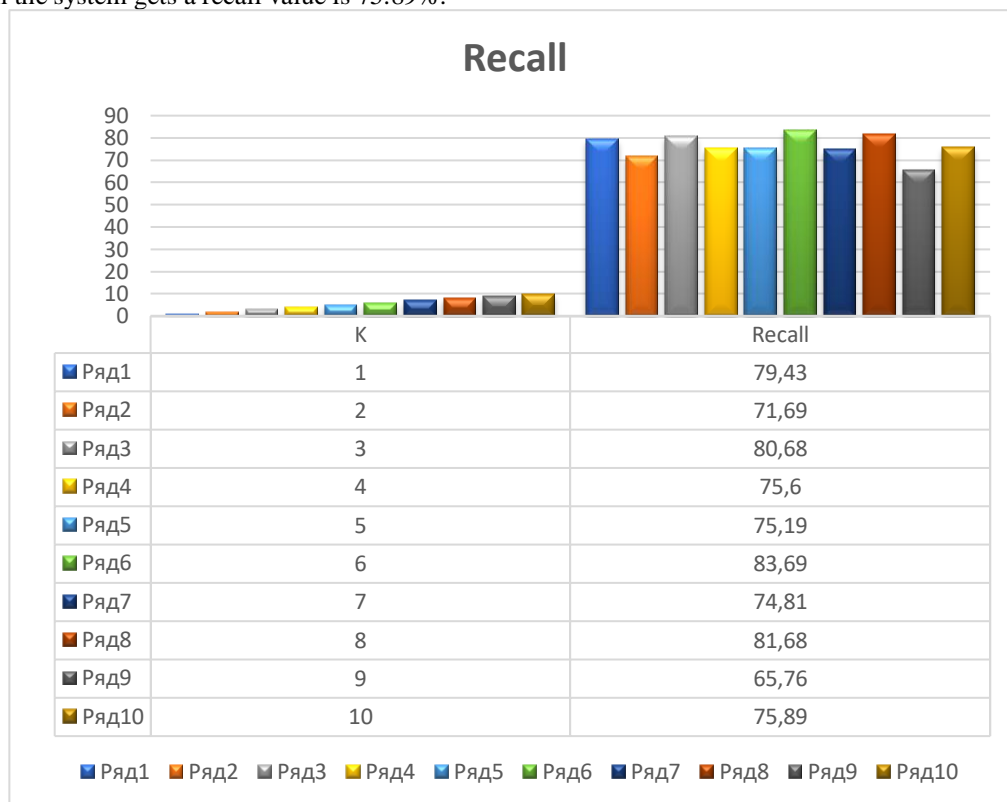■ Ряд1 ■ Ряд2 ■ Ряд3 ■ Ряд4 ■ Ряд5 ■ Ряд6 ■ Ряд7 ■ Ряд8 ■ Ряд9 ■ Ряд10

Figure 3: Instance based classifier Vs Recall

The above figure 3 the highest recall value is 83.69% which is produced by while applying the parameter k=6, the lowest recall value is 65.76% while applying the parameter k=9.

Table 3: Instance based classifier Vs Time

K	Time taken to build model(In Seconds)
1	0.19
2	0.21
3	0.49
4	0.25
5	0.23
6	0.91
7	0.24
8	0.14
9	0.36

10	1.24

The above table 3 clearly shows that the instance based classifier is taking the time consumption to build the model is different while doing the parameter tuning like K parameter. In this dataset we implement the lazy classifier while K=1 then the system takes a time consumption to build the model is 0.19 seconds, while K=2 then the system takes a time consumption to build the model is 0.21 seconds, while K=3 then the system takes a time consumption to build the model is 0.49 seconds, while K=4 then the system takes a time consumption to build the model is 0.25 seconds, while K=5 then the system takes a time consumption to build the model is 0.23 seconds , while K=6 then the system takes an a time consumption to build the model is 0.91 seconds, while K=7 then the system takes an a time consumption to build the model is 0.24 seconds, while K=8 then the system takes an a time consumption to build the model is 0.14 seconds, while K=9 then the system takes an a time consumption to build the model is 0.36 seconds, and finally while K=10 then the system takes an a time consumption to build the model is 1.24 seconds.
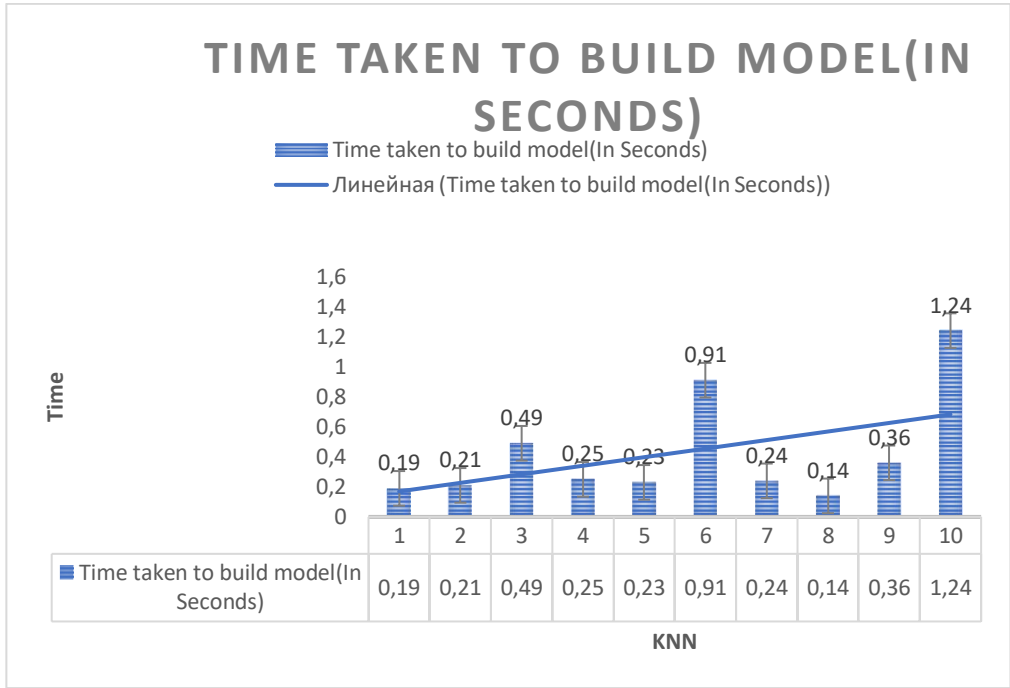

Figure 4: Instance based classifier Vs Time Consumption

The above figure 4 shows that the K=10 model takes more time to build the model is while applying the k=10 and very low time consumption model is k=8.

4 Conclusions

The System concludes that the highest accuracy value is 81.68% which is while applying the=7k=6 and the lowest accuracy value is 65.6% when apply the k=7. The highest precision value is 81.68% while applying the k=1 and very lowest precision value is 73.69% lies on k=2 and k=9.The highest recall value is 83.69% which is produced by while applying the parameter k=6, the lowest recall value is 65.76% while applying the parameter k=9. The K=10 model takes more time to build the model is while applying the k=10 and very low time consumption model is k=8.

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