Machine Vision for Automatic Quality Control of Uni-directional Tape Production

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Abstract

The quality of uni-directional tape in a production process is affected by environmental conditions like temperature and production speed. Machine vision algorithms on the scanned images are deployed in this context to detect and classify tape damages during the manufacturing procedure. We perform a comparative study among famous feature descriptors for fault candidate generation, then propose own features for fault detection using various machine learning techniques. The empirical results demonstrate the high performance of the proposed system and show preference of random forest and canny edges for classifier and feature generator respectively.

1. Introduction

Unidirectional Tapes (UD-Tapes) are thermoplastic composite comprised of reinforced fibers usually of the type glass, carbon, or natural fibers, and prove increased reinforcement when it comes to composite markets. Also, the cost for the production of two-dimensional preforms is 30% less than any other woven fabric-based organic composites (Kropka et al., 2017). These properties of a TPC, promise an alternative option to reinforced sheets along with a minimum scrap rate and a decreased production cycle time. Today, with numerous applications in lightweight series production, an evolution of a more mature supply chain has begun. Thus, it is adopted in many applications of the car industry like central floor, door panel, and wheel rim. The production of these tapes is influenced by manufacturing processes thus providing an enormous challenge to process controls such as quality assurance. The poor quality of the tapes lowers the quality of the final product. Automatic systems are needed to be developed to control the quality of UD-tape manufacturing. Advanced vision-based technologies allow a better understanding of the production process. The concept of machine-based vision begins with individual features analyzed and accordingly foresees the end value product. The data gathered from a UD-Tape helps to understand the debilitating defects, e.g., local fiber deviations, porosities, dents. Thus, sensory augmented data represents the real-world events and physical characteristics of structures and processes. Thermographic cameras generate thermal images by receiving reflected heat energy exposed from an infra-red source. It represents a visual picture of temperatures over a large area. It is a non-destructive imaging method capable of catching moving targets in real-time (Hartman, 2000).

Detecting faults and other anomalies are a part of the regular visual inspection process. With technological advancement, we make use of optical units to perform an autonomous visual inspection and store this information into a database.

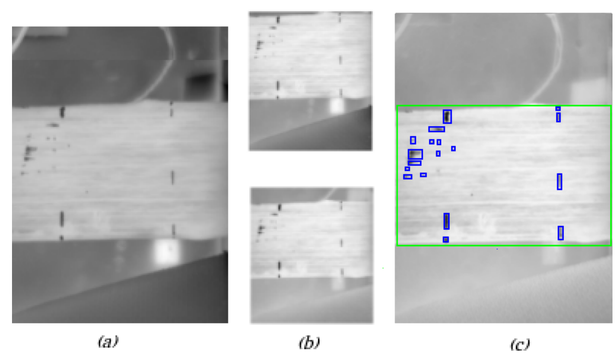


Figure 1. The challenges of this work are stated. A vision-based thermography system is used to control the quality of a tape production process. A poor tape image captured by the thermography system is shown in (image(a)). The position of the tape in the image is changing due to the vibrations occurring in the production line (image(b)). Markers are made on the tapes to track the faults in them. These markers, as well as probable faults appearing in diverse shapes and sizes, must be detected.

Finding the location of the tape and improving the visual quality in the input image are two main primary concerns for preprocessing of the UD-Tape images. Also, understanding the foreground and the background plays a key role in the identification of the visual area. Feature descriptors are exploited to revolve around autonomous systems and visual inspection. Given an attempt towards digital image pattern recognition, it is more important to understand the efficiency of features (i.e., discrimination capability over target classes) (Berger et al., 2017). Figure 1 shows the challenges we want to tackle in this paper. The quality of input

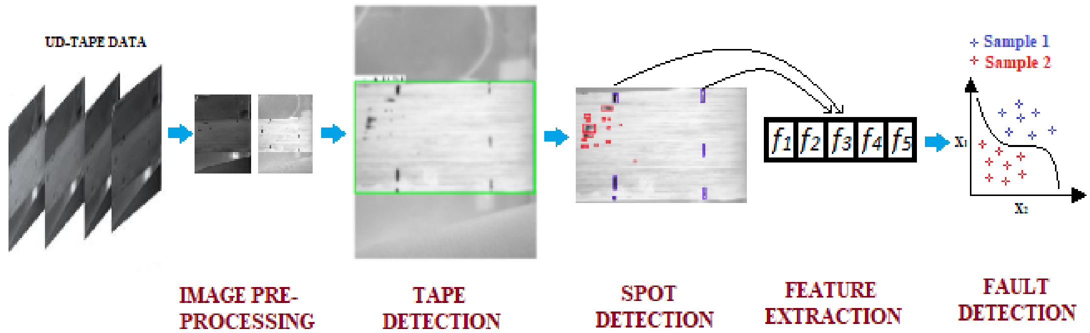


Figure 2. The proposed framework for automatic fault detection in UD-Tape production process is shown. First, the input frames from the optic sensor are enhanced, and then within the enhanced image, the tape is located using a machine vision technique. Afterward, the spots on the tape image are detected and from each point, features are extracted and forwarded to a machine learning module to classify these spots into tape faults and intentionally created markers.

images is most likely poor and they should be enhanced to improve the overall accuracy of the system. Since the location of the tape within the image is changing figure 1.b, an automatic module is required to find the location of tape and remove the background. Figure 1.c shows some spots over a tape after production. They have been highlighted by red and blue colors showing tape faults and markers respectively. Note that to trace the position of the faults over the tapes, some markers are intentionally added to the tapes after the production process. An automatic system is required to detect these spots, markers, and accordingly, find faults among them. In this paper, vision-based methods on thermographic images are deployed to detect and classify the tape faults and markers during the tape manufacturing process. A comparative study among famous feature descriptors are undertaken to generate fault candidates, then tested using machine learning techniques based on some features to recognize the faults and markers.

The rest of the paper is organized as follows: A general overview of related work is given in Section 2. Section 3 proposes our algorithms for the tape fault detection problem. Experimental results of this research are reported in Section 4 and finally, Section 5 concludes this paper.

2. Related Work

This section gives a literature review including state-the-art for similar works to this research. Prognosis enhances the structural monitoring and qualitative planning on composite materials from a production perspective. The main motivation for our work can be seen in (Berger et al., 2017), as it presents the development of a process integrated quality control of continuous fiber-reinforced plastics(CFRP) using eddy current inspection.

Non-destructive evaluation techniques help in determining the properties of UD-tapes showing different defects such as fiber misalignments, porosities and delaminations (Grosse et al., 2016). These methods used for inspection of composites are largely based on the detection and analysis of delamination in composite materials (Aymerich & Meili, 2000).

Thus leveraging learning approaches will help analyze relevant component characteristics. Furthermore, with the extraction of features for efficient production of composites, the vast space of composite structure data can be explained (Vikram Gopal, 2015). As, much research is being done on prognosis of composites laminates based on machine learning techniques, the area of unidirectional composite is untapped yet. One such research (Liu et al., 2017) shows the prediction of delamination size using machine learning models, such as Linear model, Support Vector Machines, and Random Forests. Here the authors present damage quantification from the delamination area in X-ray images.

To perform an automated classification one needs to extract features from images and then apply classification algorithms to those extracted features. In (Kitanovski et al., 2011), the authors propose a comparison between different feature extraction algorithms. Local HOG features of defective region of interest obtained from thermography processing of in carbon fiber-reinforced plastics is presented in (Erazo-Aux et al., 2019). They are robust to illumination change but cannot be applicable to the marker/fault classification. Similarly, a machine vision-based process feedback is shown in (Cheng & Jafari, 2008). Here, the features are measured in terms of height and volume of solid forms in manufacturing applications.

In this paper we used six feature extraction methods over a set of thermographic images and then classified them via different classification algorithms.

3. Proposed Method

In this section, we explore the characteristics of UD-Tape sensor data. Figure 2 shows the proposed framework for automatic inspection of tape manufacturing process based on thermographic sensors. We start with enhancing the visual quality of the input sequence and then prioritize a region of interest, aiming to find the location of the tape within the image. It is followed by exploiting feature extraction techniques to detect the intentionally made markers as well as the tape faults. Finally, this system extracts some features from the markers and faults and forwards them to machine learning models for classification and recognition.

The captured images suffer from a poor illumination condition. To elevate the overall detection of the proposed system, it is necessary to enhance the quality of the images before further steps. Thus we look into Histogram equalization (Han et al., 2011), where in we equalize luminance, brightness and contrast values, of a poor quality image to that of the good quality image. Finally, the pixels' value of all input images fall between 0-255.

As part of image enhancement, we take into account different image filtering techniques for reduction of noise or any irregularities. Here, we have studied different image enhancement techniques and chosen the one that gave relevant features corresponding to our requirement. We begin with performing morphological operations such as erosion, dilation, and finally with the help of a linear filter, in convolution with a 1x1 structuring element, we were able to reduce its trivialness and tweak an image into yielding us the right results.

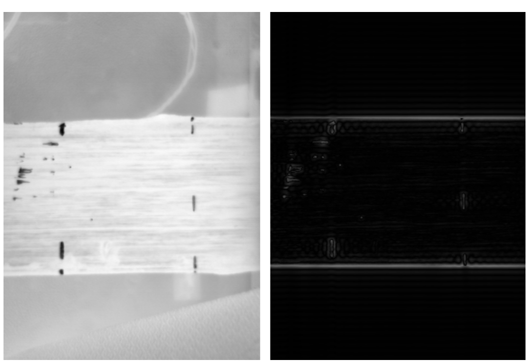


Figure 3. Tape detection using the Grab-cut method is presented. The output mask image (right image) shows the upper and lower margins of the tape (left image) by two lines. These lines are normally thicker than one pixel. For each margin, the middle line is selected as the tape border.

Two algorithms for prioritizing the region of interest have been exploited. Grab-Cut algorithm and Faster-RCNN. The Grab-Cut algorithm implements a Gaussian Mixture Model (GMM) (Wu et al., 2012) to create labels and cluster pixels according to their intensity. If a greater dissimilarity is found, then those pixels are segmented as either foreground or background. Figure 3 shows the results achieved from the interactive grab cut algorithm.

Alternatively, in the context of tape detection, a famous deep neural network (Ren et al., 2015) has been employed to achieve a generalized model for tape detection. Faster-RCNN is employed, because of its precision and fast running in the test phase. This method uses convolutional neural networks for object detection and classifications to improve the performance of recognition. The manually labeled tapes in diverse images are fed to the classifier for training. The result of Faster-RCNN classifier is shown in Figure 4.

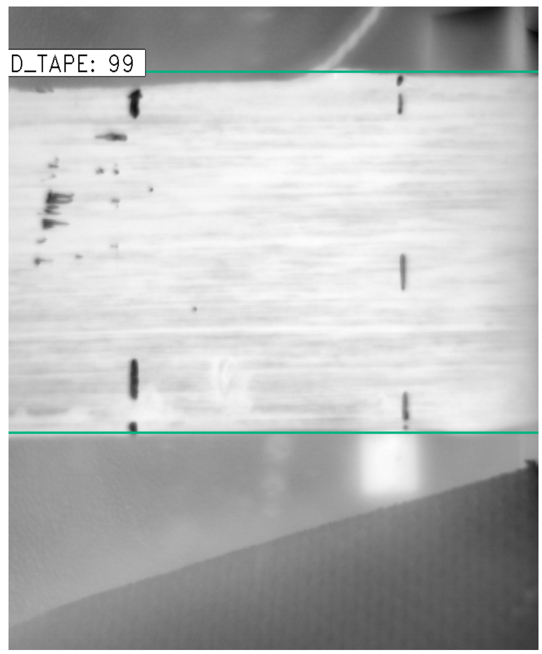
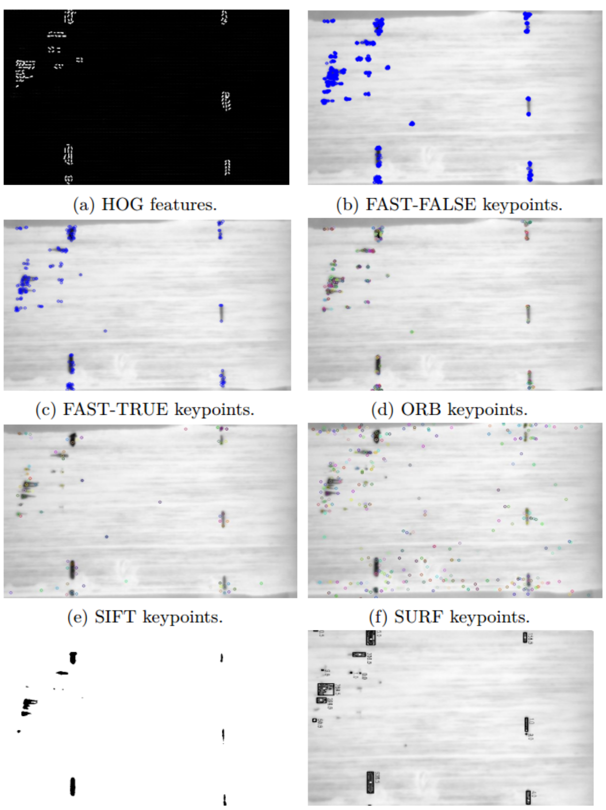


Figure 4. Tape detection using Faster-RCNN technique with a confidence score of 99 is shown. This classifier has been trained with various tapes and finds their location in the test phase.

For detection of voids over tapes, we have explored different feature descriptors which are listed as follows: Histogram of oriented Gradients (HOG) (Öztürk & Bayram, 2018), determines the orientation and magnitude of key points in an image. Features from Accelerated Segment Test (FAST) (El-Gayar et al., 2013), starting with a round mask over a pixel, which is then compared to the following consecutive pixel using a comparison function. The algorithm focuses on corners than that of edges and is based on SUSAN(corner criteria). Oriented FAST and rotated BRIEF (ORB), makes use of the FAST feature descriptor to get key points and with the help of Harris corner measure (Amaricai et al., 2014), results in multi-scale features. Scale Invariant Feature Transform (SIFT) (Öztürk & Bayram, 2018) is a texture-based algorithm that starts with comprehending local features and comparing the neighboring pixels. Respectively, the key points are eliminated with key points examination. Speed-up robust features (SURF) (El-Gayar et al., 2013), is a three-step feature extraction method that comprises of detection, matching, and description. SIFT and SURF employ detection in the same ways but with a slight difference in image pyramids. Canny edge detection (Ramesh Jain, 1995) makes use of multi-stage algorithms to detect edges present in images. Figure 5 shows the application of these features for void detection. According to this figure, HOG shows better results than FAST, ORB, and SIFT but has a large number of false positives. The SURF algorithm was not much successful as it detected many non-void regions, whereas the Canny edge detector detects the voids very successfully.



(a) HOG features. (b) FAST-FALSE keypoints. (c) FAST-TRUE keypoints. (d) ORB keypoints. (e) SIFT keypoints. (f) SURF keypoints. (g) Binary input image. (h) Canny edge detection.

Figure 5. Visual results of a comparison among Histogram of oriented Gradients, Features from Accelerated Segment Test, Oriented FAST and rotated BRIEF, Scale Invariant Feature Transform, Speed-up robust features, and Canny edge detection for marker and fault detection. Canny edge shows the best results among them. This is because it reflects markers and faults very well and it doesn't produce redundant false alarm information.

We have used supervised machine learning techniques to simultaneously detect the faults and markers over the located tapes. A set of geometrical features namely shape, size, relative location, and aspect-ratio of the markers/faults have been calculated and used to make a feature set for the fault detection task. This feature set is then, in a random cross-validated method fed to machine learning models for training and test. The details of this experiment are given in the Results Section 4.

4. Evaluation and Results

To evaluate the proposed system, we have used 450 thermographic images of size 768x1024 pixels. For the evaluation of tape location algorithms, IoU measure (Intersection over union) (Gan et al., 2019) is used to decide if the predicted output corresponds to the ground truth. The formulation of IoU is given below: In the tape location scenario, a true

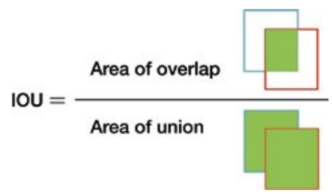


Figure 6. Basic idea of Intersection over union.

positive (TP) occurs when a full tape exists in the image if the system detects it correctly i.e., IoU is greater than 0.5. Similarly, false positive (FP) happens when the system detects a non-tape object as the tape i.e., IoU is smaller than 0.5. and a false negative (FN) occurs when a tape exists in the image and the system cannot detect it.

We explore Precision, Recall, and F_1 to evaluate algorithms within the proposed framework. Precision is the measure of correctness of an algorithm. When it comes to machine learning models precision and recall help evaluate the correctness of our model. In our case, precision is the relevant classification results and recall refers to relevant predicted results (Gan et al., 2019).

$$Precision = \frac{T_P}{T_P + F_P} \tag{1}$$

$$Recall = \frac{T_P}{T_P + F_N} \tag{2}$$

$$F_1 = 2 \times \frac{Recall \times Precision}{Recall + Precision} \tag{3}$$

In our fault detection scenario Section 3, a true positive (T_P) and a false positive (F_P) occurs when a detection is classified as a marker or a fault respectively. Similarly, a true negative (T_N) or a false negative (F_N) happens when a marker/fault is misclassified.

4.1. Tape Location Results

In this section, the results of our experiments for the tape location algorithms with outputs from calculating the IoU of the two algorithms, are compared to understand better. The experimental results of the grab-cut algorithm and Faster-RCNN are shown in Table 1. Because of photography expenses, the dataset containing valid images is small , hence the grab-cut algorithm performed better than Faster-RCNN. However, the difficulty arises when the computational complexity and time constraint increases. As the number of images is constrained, thus there is no such requirement for a black-box analysis. We have used 100 images for Tape detection. The deep classifier explained in Section 3, is trained on 60 augmented images and the classifier is able to detect UD Tapes with a 95.7% accuracy rate. It is expected that with more data the performance of Faster-RCNN is improved.

Table 1. Quantitative IoU results for 10 predicted images for the both tape location algorithms i.e., Grab-cut and Faster-RCNN are shown. The Grab-cut shows averagely better results than Faster-RCNN.

	Grab-cut	Faster-RCNN
Image 1	0.8564	0.8927
Image 2	0.8574	0.0104
Image 3	0.9001	0.9221
Image 4	0.8953	0.9417
Image 5	0.8665	0.8955
Image 6	0.9081	0.9483
Image 7	0.8465	0.7566
Image 8	0.9126	0.9117
Image 9	0.8733	0.7951
Image 10	0.8574	0.9130

Our experiments show that Grab-cut algorithm slightly outperforms Faster-RCNN with an average IoU result of 0.8773 while the Faster-RCNN shows an average IoU equal to 0.808.

4.2. Fault Detection Results

Table 2 shows the performance of well-known low-level feature extraction algorithms. There is no single method sufficient enough to detect all cases, hence the comparison is based on the number of correctly identified voids/dents present in the UD Tape data set in regard to the total number of dents/voids present. The HOG and SIFT features are able to detect the main voids present but due to some local vicinities, there are too many false positives as compared to the others. In contrast, Canny edge detector outperformed all the other descriptors, although due to intensity variations in-between close by pixels, it detects rarely wrong regions as positive. As a result, canny edge detector is chosen for void detection.

Table 2. Quantitative results of the experimented feature descriptors to detect the markers and the faults on a UD-tape are shown. Canny edge detector shows the best performance in terms of TP and FP.

Feature descriptor	Total number of detections (TP+FP)	Correctly detected (TP)	Incorrectly detected (FP)
HOG	14	9	5
FAST-TRUE	254	20	234
FAST-FALSE	1650	20	1630
SIFT	87	17	67
SURF	295	20	275
ORB	318	20	298
CANNY	24	20	4

We have divided these features into two classes as *'marker'* and *'non-marker/faults'*. The non-marker class represents the production fault which is assigned to 0. Whereas the marker class is set to 1.

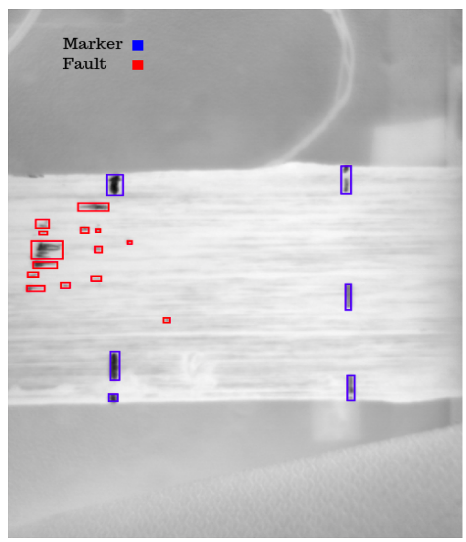


Figure 7. Classifying the detected spots into markers and faults using a supervised machine learning method. For this task 6 classifiers namely Support Vector Machine, Logistic-Regression, Bayesian Network, Random Forest, Decision Tree and K-Nearest Neighbours have been used.

In our initial experiments, we obtained poor overall results because of the highly unbalanced distribution of data over the target classes. Figure 8 shows initial data distribution, wherein the number of samples present is 2192, however, there is more number of non-marker class samples than that of a marker class. Hence, to have a stratified distribution, we consider a similar number of marker class to that of non-

Table 3. Comparison of different machine learning classifiers i.e., Support Vector Machine, Logistic-Regression, Bayesian Network, Random Forest, Decision Tree and K-Nearest Neighbours for tape marker/fault classification. Logistic-Regression and Random Forest show better performance among them in terms of Accuracy, Precision, Recall and F1-score.

Classifier models	Accuracy	Precision	Recall	F1-score
SVM	91.11%	91%	91%	91%
Logistic-Regression	97.05%	97%	97%	97%
Bayesian Network	91.11%	91%	91%	91%
Random Forest	97.05%	97%	97%	97%
Decision Tree	91.17%	91%	91%	91%
K-Nearest Neighbour	91.11%	91%	91%	91%

marker class samples. Accordingly, this can be observed from Figure 9.

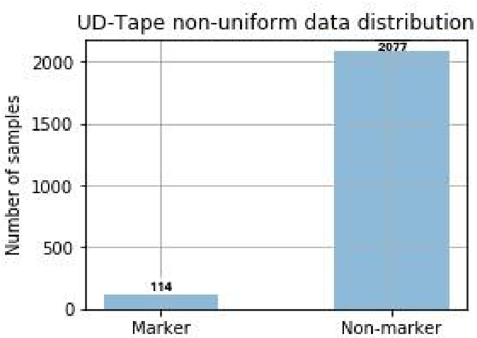


Figure 8. Initial non-uniform distribution of data over the two classes of markers and tape faults is shown. For one class, very poor classification results were obtained.

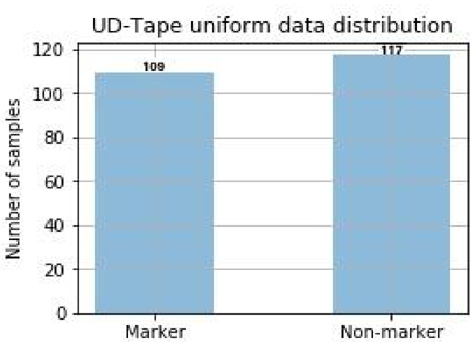


Figure 9. Uniform distribution of data over two classes of markers and tape faults is used. Thus, the overall performance of classification has been improved.

As accuracy would not be sufficient, hence we take the F_1-score as well into consideration. Table 3 shows the outcome of machine learning models using a uniform distribution of data set. Based on these results we observe that all the models performed comparable well to each other. In conclusion, logistic-regression and random forest classifier stood out and this can be seen in Figure 10.

For non-uniform distributed data set, we have considered micro averaged accuracy for each class outcome because it is expected to perform better for an imbalanced classification task (García et al., 2007). Figure 11 shows the corresponding performance.

5. Conclusion

This paper has proposed an automatic machine vision-based system to monitor the quality of UD-Tapes in the manufacturing procedure. With prioritizing our region of interest using detection algorithms, the tape is located and prepared for feature extraction. We have implemented some of the traditional descriptive feature descriptors for fault candidate generation and found Canny edge detector as the best one. Accordingly, relevant geometrical features of faults are extracted. The proposed framework can work with different machine learning strategies for classification over markers and tape faults. It is concluded that Logistic-Regression and Random-Forests performed better, in terms of micro averaged accuracy and F_1. For future research, one should focus on feature extraction algorithms to understand fiber alignment and delamination. This area of UD-Tape assessment could help to analyze the material grade. The distribution of data should be prepared such that machine learning models could perform multi-classification approaches showing real like scenarios and clustering patterns from UD-Tape features, thus enabling an automated feedback system to improve the production quality of the Tapes.

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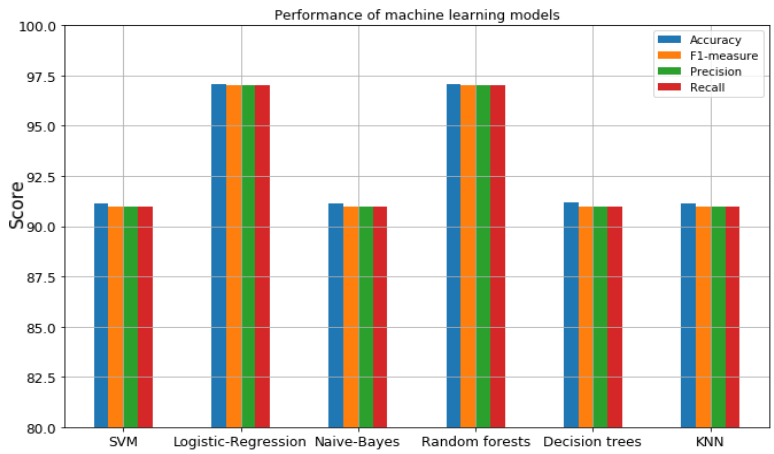

Figure 10. A comparison among machine learning models with the uniform distributed data set is shown. Random forest and logistic regression outperform the other classifiers.

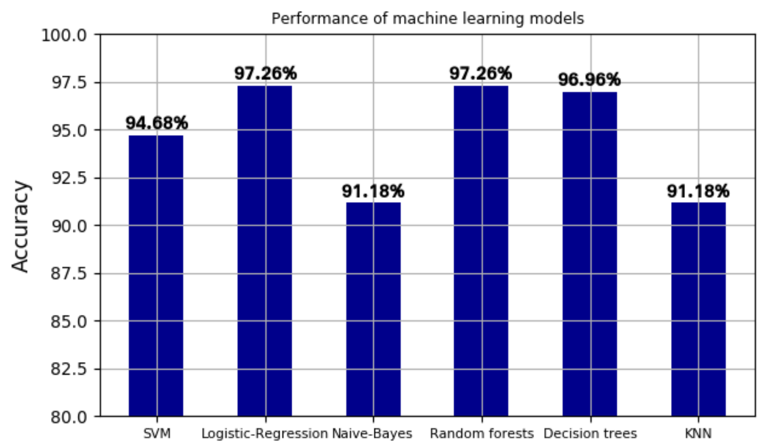

Figure 11. The performance of various machine learning models with non-uniform data set is shown. Although the overall performance is high but, the results for one class are poor for all the classifiers.

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