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Automated Classification Framework for Road Condition Detection and Maintenance Prediction

Suwarna Gothane[1], Dr. M. V. Sarode[2], Dr.V.M.Thakre[3]
Associate Professor[1], Head of CSE Dept[2], Professor[3]
CSE Dept[1,2,3], CMR Technical Campus, Hyderabad[1],Research Scholar, Sant Gadge Baba Amravati University,India[1].
Government Polytechnic, Yavatmal, India[2].
Sant Gadge Baba Amravati University India[3].
gothane.suvarna@gmail.com[1],mvsarode2013@gmail.com[2], vilthakare@yahoo.co.in[3]

Abstract-The road transport is a substantial method of transportation in the faster growing countries. Nonetheless the faster transport on the road surface depends on the road condition. Thus making the road ready to match with the growing traffic conditions and growth of the nation is the most crucial factor. Nevertheless, in the due course of the time, the road surfaces tend to decay with high traffic volume. Hence this adds to the maintenance tasks. The authorities in every nation deploy high work force and time to maintain and rebuild the road conditions. It is been observed that the preventing measures on the road repair can make the road surface last longer and can reduce significant time for the maintenance needed for high damage rebuild operations. Nonetheless, the potholes causing major delinquent on the road surfaces can easily visible but the cracks on the road, which will significantly become a pothole cannot be always seen by human eyes. Also, the availability of the already made patch works makes the task difficult further. In, addition the maintenance tasks demands a suitable condition of the weather, which is difficult to predict. Situations have proven that the maintenance work started with no knowledge of the weather had to abort and caused further delay in the task resulting into further decay in the road conditions. Thus it is the demand of the recent research to provide the prediction of the road condition in order to detect the potholes to be given higher priority, cracks to be considered for immediate repair and patch works to be ignored during the automation. Also, the based on the nature of the damage or repair task, the weather conditions are to be analysed and the recommendation on the start date of the maintenance task also to be predicted. A number of research attempts are made in order to analyse the road conditions. Nonetheless, the automation of the predictive maintenance scheduling is not been address. The major outcome of this work is to build an automated framework to analyse and predict the road damages and recommend the schedule maintenance tasks with 100% accuracy in order to make the world with better surface transport capable.

Keywords-Predictive Classification; Automation of Repair Schedule; Weather Information Inclusion; Road Defect Rule Engine; Repair Recommendations; Comparative Defect Analysis

1. INTRODUCTION

The engineering foundations like concrete surface, beams and other constructions are vulnerable to stress on the surface and can lead to the microscopic level cracks. The cracks make the surface stiffness weak. The notable work by Bernard Budiansky et al. [1] and the work by Jacob A et al. [2] have demonstrated the effects of cracks over the time on any surface. The cracks eventually lead to the potholes, thus causing further decay on the road condition. Thus it is recommended by various research attempts to detect the cracks with the expected damage and prevent the future failures. The work by D. Dhital et al. [3] has made the thought confirmed with experimental results. The work by Dhital et al. [3] has also defined the newer dimensions of testing the cracks by the means of expansion towards the bigger damages like potholes. Various parallel research attempts are made in order to detect the cracks on the surface. The work by Baohua Shan et al. [4] have demonstrated that the use of crack types, number of cracks on a single frame or width of the cracks can help in determining the possible expansions. Also, another notable work by Suwarna G. et al. [5] has proven the parameter collection process is the core of the complete predictive or analytic analysis for potholes,cracks or patch detection. Nonetheless, the detection process is subjected to accuracy of detection of the defect natures and the recommendations for repair. Nevertheless, the issue is not been addressed by the parallel research attempts. Thus this work deploys an automatic detection of road surface conditions and predicts the nature of the damages. Also this work analyses the weather condition for making the accurate repair schedule for the damages to be addressed.

The rest of the work is furnished such as in Section – II the outcomes of the parallel research is been analysed, in Section – III the proposed framework is been projected with the significance and benefits, in Section – IV the proposed predictive algorithm is analysed, the obtained results by the framework is analysed and discussed in the Section – V, the comparative benefits of the proposed framework is discussed in the Section – VI and the work finalized the conclusion in the Section – VII.

2. OUTCOME FROM THE PARALLEL RESEARCHES

Potholes, cracks and patch work detection methods are highly popular and widely accepted. Thus various parallel researches have addressed the issue and tried solving the problem using various methods. This section of the work compares various methods such as camera image based analysis, Infra-Red image based analysis, ultrasonic image based analysis, TFD image based analysis and laser image based analysis in this section with significant scopes for improvements.

A. Camera Image Based Detection

Firstly and one of the most widely accepted methods is the camera image based detection method. The notable work demonstrated by Zhang Yiyang et al. [6] has demonstrated the process of capturing the image and do pre-processing in order to make the images sharper. These noise free sharp images are used in order to extract the parameters. Nevertheless, the extracted parameters are subjected to availability in all conditions, thus making the model less applicable for all datasets.
Also, the notable work by R.S. Adhikari et al. [7] has proposed to incorporate the defects on the road surface by the numeric levels in order to justify the detection process. Nonetheless, the framework is pre-processing dependent and must be accurate to determine the numeric class values.
Further, P.K. Biswas et al. [8] defined a newer dimension of the image based analysis by the use of 3D images. The proposed model demonstrated significant accuracy due to the use of neural network models. However, the model demands Arial and surface images in order to create a depth view of the cracks.

B. Infra- Red Image Based Detection

Secondly, the alternative method for camera image based detection is the infra-red image based analysis. The notable work by M. Rodriguez-Martina et al. [9] has demonstrated the use of thermography based information use for detection and orientation of the cracks. The method is highly accepted in the situations where IR equipment is available.

Another contribution by Patrik. Broberg et al. [10] proposed a framework for detecting the cracks or the potholes by detecting the notches in the IR images.

Also, the work by Welding et al. [11] [12] have demonstrated the detection of potential defects on the road surface by classification methods.

The most recent outcome by the work of Will S.M et al. [13] has demonstrated the use of reflective IR sources to detect the depth of the potholes and calculate the potential depth of the cracks leading towards the potholes. This method can also separate the patchworks from the cracks and other anomalies.

C. Ultrasonic Image Based Detection

Next, the ultrasonic image based detections are analysed. First this method was proposed by J.R. Lee et al. [14]. This method uses a piezoelectric air coupled system to detect the cracks using the UFT algorithm.

Further, the work by Giovanni Pascale et al. [15] has significantly improved the methods of detecting the crack depths in the existing frameworks.

The nature of the cracks can be important to decide the nature of the damages can be caused by the same crack. The notable work by Hiromi Shirahata et al. [16] demonstrated the process of successfuldetermination the nature of cracks and further use the information to prioritise detection.

D. Time of Flight Diffraction Image Based Detection

The TFD based detection method uses a set of images over the time to analyse the nature of the cracks created and the nature of the expansion of the cracks. The work by ThourayaMeraziMeksen et al. [17] has demonstrated the method first and obtained satisfactory results.
The work by Malika Boudraa et al. [18] uses the same principle and has made significant improvements in decision making systems for the repair or patch works. Henceforth, with the light of the parallel research outcomes, this work furnishes the novel framework in the next section.

3. PROPOSED FRAMEWORK

In this section of the work, the proposed novel framework components are been discussed.

The proposed framework [Figure – 1] is built with an objective to deliver the most accurate detection of potholes, cracks and patchworks on the road surface. After the detection of the nature of the defect, the automatic maintenance schedule is proposed. While making the repair or the maintenance schedule, the weather information is to be analysed in order to avoid the interruptions caused due to bad weather conditions. The components of framework with the functionalities are discussed here.

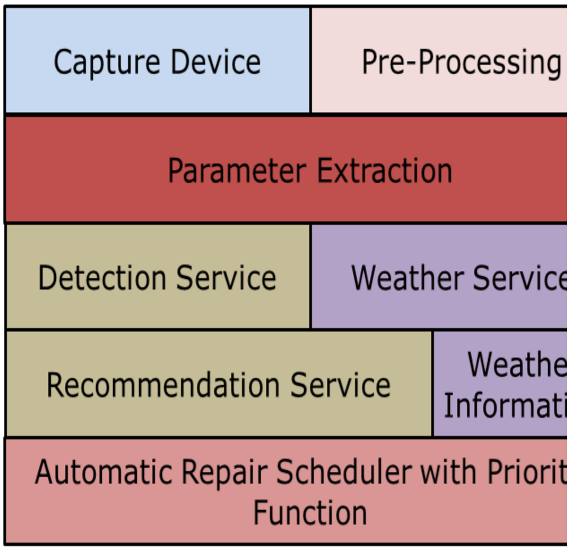

Fig.1 Proposed Novel Framework for Maintenance Prediction

A. *Capture Devices*

The capture devices are often known as the camera devices for capturing the road images. The camera devices are usually mounted on a vehicle in order to collect number of images in a shorter duration of time. The capture device makes a significant difference in terms of the accuracy of detection for the complete framework. The work by Aaron Deever et al. [19] has demonstrated a framework in order to compare and select the most suitable capture devices. The parameters of that finding are listed here[Table – 1].

TABLE 1. CAPTURE DEVICE CHARACTERISTICS

Meta Data Parameter	Parameter Description
MAKE	The company information for the authenticity measure
MODEL	The unique number of the capture device model
DATE_TIME_ORIGINAL	Availability of time and date information of the image data first capture
EXPOSURE_TIME	The duration for the image data to be exposed to the sensors
FNUMBER	The focal length information during the capture process
FLASH	The intensity of the artificial lights during the image capture
DATE_TIME_LAST	Availability of time and date information of the image data last modified

Thus, the availability of these parameters can help in comparing the suitable capture device and make the further processing less noise and blur affected.

B. *Pre-Processing*

The pre-processing of the captured image data is ominously important in order to reduce the noise and blur effects from the images. The notable work by Suwarna et al. [5] has demonstrated the use of moment algorithms to detect the noise and blur types dynamically and remove those defects in the images. This work re-utilizes the findings from the previous work.

C. *Parameter Extractions*

The detection of the potholes, cracks and patchworks on the road surface can be detected by analysing the images. The detection has to depend on certain parameters in order to make the decision. Thus, the formulation of the parameters and the extraction of those parameter values from the image information are highly crucial. The novel framework by Suwarna et al. [20] has demonstrated a considerably high accuracy of parametric value extraction from the image data. In this work, Suwarna et al. [20] has also designed a novel parameter set for improving the detection accuracy. This work re-utilizes the findings from the previous work.

D. *Detection Service*

The detection services module in this framework classifies the defects based on the nature into three major categories as potholes, cracks and patchworks.

In this module, firstly classifications of the defects are identified [Table – 2].

TABLE 2. DEFECT CLASSIFICATION

Class Name	Defect Type
Class – A (1)	Patchworks
Class – B (2)	Cracks
Class – C (3)	Potholes

The framework deploys the following table of rule base to categorise the defects [Table –3].

TABLE 3. RULE ENGINE INFORMATION

Rule SetNumber	Rule Number	Parameter Name	Value Range	Detect Class
Ruleset – 1	Rule - 1	longSlope Max:	1.36	Class – A
	Rule - 2	perpendicularSlope Max:	11.16	
	Rule - 3	Object Number Max:	1	
	Rule - 4	Max distance between Objects Max:	571.28	
	Rule - 5	Perpendicular distance at midpoint Max:	269.12	
	Rule - 6	Average perpendicular width Max:	90.55	
	Rule - 7	Area Max:	23833	
	Rule - 8	longSlope Min:	-1.92	
	Rule - 9	perpendicularSlope Min:	-13.08	
	Rule - 10	Object Number Min:	1	
	Rule - 11	Max distance between Objects Min:	167	
	Rule - 12	Perpendicular distance at midpoint Min:	38.28	
	Rule - 13	Average perpendicular width Min:	37.26	
	Rule - 14	Area Min:	8615	
Ruleset – 2	Rule - 15	longSlope Max:	1.66	Class – B
	Rule - 16	perpendicularSlope Max:	22.95	
	Rule - 17	Object Number Max:	1	
	Rule - 18	Max distance between Objects Max:	1010.96	
	Rule - 19	Perpendicular distance at midpoint Max:	626.53	
	Rule - 20	Average perpendicular width Max:	240.68	
	Rule - 21	Area Max:	139078	
	Rule - 22	longSlope Min:	-2.3	
	Rule - 23	perpendicularSlope Min:	-7.32	
	Rule - 24	Object Number Min:	1	
	Rule - 25	Max distance between Objects Min:	295.11	
	Rule - 26	Perpendicular distance at midpoint Min:	23.23	
	Rule - 27	Average perpendicular width Min:	37.21	
	Rule - 28	Area Min:	27436	
Ruleset – 3	Rule - 29	longSlope Max:	1.88	Class – C
	Rule - 30	perpendicularSlope Max:	7.91	
	Rule - 31	Object Number Max:	1	
	Rule - 32	Max distance between Objects Max:	1529.93	
	Rule - 33	Perpendicular distance at midpoint Max:	880.17	
	Rule - 34	Average perpendicular width Max:	522.15	
	Rule - 35	Area Max:	686531	
	Rule - 36	longSlope Min:	-1.59	
	Rule - 37	perpendicularSlope Min:	-12.77	
	Rule - 38	Object Number Min:	1	
	Rule - 39	Max distance between Objects Min:	572.61	
	Rule - 40	Perpendicular distance at midpoint Min:	150.92	
	Rule - 41	Average perpendicular width Min:	171.29	
	Rule - 42	Area Min:	142059	

Henceforth this rule based engine will detect the defect class for further analysis.

E. Weather Service

The next component in this framework is the weather component. This component integrates with the external weather API can generate the weather prediction report to support the maintenance schedule. The architecture of the external service, Open Weather Map is furnished here [Figure – 2].

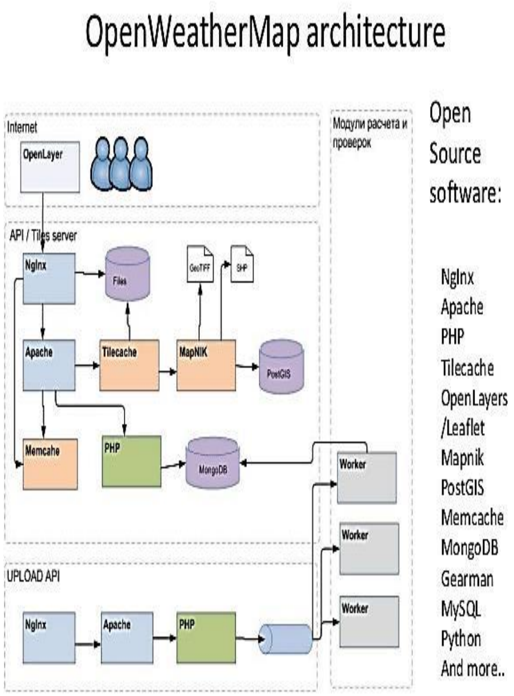

Fig.2 Open Weather Map Architecture

Further, the OpenWeatherMap is integrated to this proposed novel framework. The API description is formulated here [Table – 4].

TABLE 4. API DESCRIPTION

API Call Type	API Call Description	API Call Details
By CITY Name	Call by city name or city name and country code. API responds with a list of results that match a searching word.	api.openweathermap.org/data/2.5/weather?q={city name},{country code}
By CITY ID	Call by city ID. API responds with exact result.	api.openweathermap.org/data/2.5/weather?id=2172797
By Coordinates	Latitude and Longitudecoordinates of the location.	api.openweathermap.org/data/2.5/weather?lat={lat}&lon={lon}
By ZIP Code	Call by ZIP Code. API responds with exact result.	api.openweathermap.org/data/2.5/weather?zip={zip code},{country code}

F. Recommendation Service

The next component in the framework is the recommendation service component. This component degenerate the recommendation for the repair work based on the highest available defect and nearing the same geodetic location. This component also supports the predictive detection of the defects. The nature of the predictive analysis is furnished below [Table – 5].

TABLE 5. RECOMMENDATION SERVICE RULES

Defect Type	Expansion Defect Type	Possibility of the Expansion	Repair Work Recommendation
Cracks	Potholes	High	Patching, Filling
Potholes	Structural Damage	High	Filling
Patches	Cracks	High	Smoothing
Cracks	Potholes	Mid	Patching
Potholes	Structural Damage	Mid	Filling
Patches	Cracks	Mid	-
Cracks	Potholes	Low	Delayed Repair
Potholes	Structural Damage	Low	Filling
Patches	Cracks	Low	-

Henceforth, by analysing the defect type and further analysing the possibilities of growth into the higher category of defects, this component generates the recommendation for repair.

G. Weather Information

The Weather information accumulated from the integrated service is formatted into the system readable and decision supportive formats. The weather information once accumulated from the external service will be stored in the following format [Table – 6].

TABLE 6. WEATHER PARAMETERS

Parameter Name	Parameter Description
RECORD.ID	Weather record id
LONGITUDE	Longitude of the location
LATITUDE	Latitude of the location
CLOUD	Availability of cloud
CURRECT.TEMP	Current temperature
MAX.TEMP	Day's maximum temperature
MIN.TEMP	Day's minimum temperature
PRESSURE	Air pressure
HUMIDITY	Humidity in the Air
VISIBILITY	Visibility in terms of distance
WIND.SPEED	Speed of the wind
WIND.DIRECTION	Direction of the wind
COUNTRY.CODE	Country code
SUNRISE.TIME	Time of Sunrise
SUNSET.TIME	Time for Sunset
CITY.NAME	Name of the City

H. Repair Scheduler with Priority Function

The final component in the framework is Repair Scheduler with Priority Function. This component generates the repair schedule for detects which are identified and recommend the repair process with the priority function value. The sample repair scheduler parameters are formulated here [Table –7].

TABLE 7. REPAIR SCHEDULER PARAMETERS

Parameter Name	Parameter Description
Defect ID	The automatic assigned ID to all the defects
Longitude	Longitude of the location, where the defect is identified
Latitude	Latitude of the location, where the defect is identified
Number of Objects	Number of defects identified in the same location
Width	Width of the identified defect
Depth	Depth of the identified defect
Area	Area of the identified defect
Priority	Repair Priority

Further, the priority function is a result of the predictive analysis system. The predictive classification analysis algorithm is furnished in the next section.

4. PROPOSED ALGORITHM

The proposed algorithm supporting the framework is elaborated here.

Step -1. Accumulate the Attributes from the Data Set
Step -2. For each attribute
 a. If the attribute is real parameter
  i. Then store into Real_table
 b. Else If the attribute is derived attribute
  i. Then store in Symbol_table
 c. End
Step -3. End
Step -4. Apply probabilistic function to calculate the change in both attribute sets
Step -5. If the change is nearly 1
Step -6. Then calculate the change rate and update the parameter values
Step -7. For each itemset in the database
 a. Classify the data items based on the rate of change of Symbol_table * 70% weight + Real_table * 30% weight
Step -8. End

The algorithm flow is also analysed graphically [Figure – 3].

Thus the use of the probabilistic function to calculate the change possibilities and the use of classification based on the derived or symbolic attributes are proven to be a significant improvement over the other algorithms.

The results obtained from the framework are discussed in the next section.

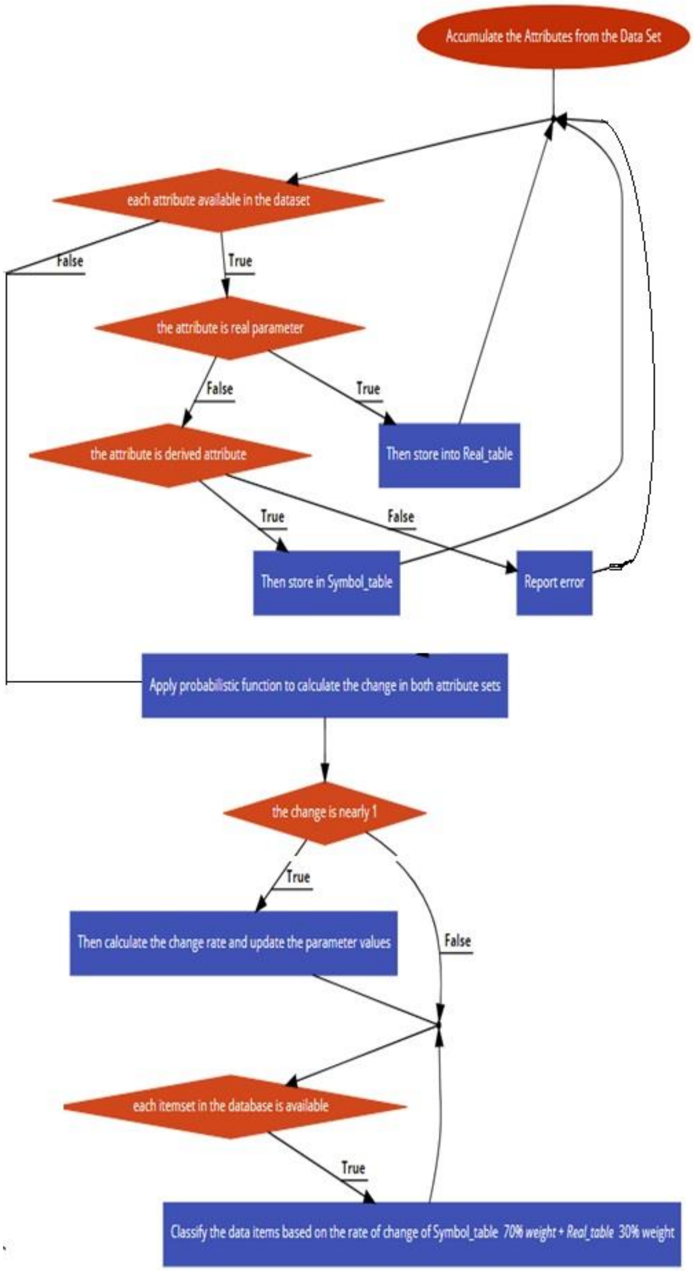

Fig.3 Flow Analysis of the Algorithm

5. RESULTS AND DISCUSSION

Henceforth, in this section of the work the results obtained from the novel framework is been analysed. The results analysis is segregated into few categories like analysis of the dataset for parametric information, predictive classification, detailed accuracy analysis, Confusion matrix analysis, Weather information results and the scheduler report.

A. Data Set Analysis

This work analyses the algorithm on three different datasets. Firstly, the datasets descriptions for algorithm applicability is analysed for Indian Surface Maintenance Authority Image Samples [Table – 8], Queensland dataset [Table – 9] and Highway England [Table – 10].

TABLE 8. DATASET INFORMATION - INDIAN SURFACE MAINTENANCE AUTHORITY IMAGE SAMPLES

Parameter Name	Descriptions
Dataset Name	Indian Surface Maintenance Authority Image Samples (ISMAIS)
Dataset Source	Indian Surface Maintenance Authority
Number of Item sets	300
Dataset ID	2016-10-12
Available for API access	No
Data Format	Images

TABLE 9. DATASET INFORMATION – QUEENSLAND IMAGE SAMPLES

Parameter Name	Descriptions
Dataset Name	Queensland Dataset (QesD)
Dataset Source	Queensland, AU
Number of Item sets	100
Dataset ID	d618ce2e-7d29-4569-97bd-d97bd5831924
Available for API access	Yes
Data Format	CSV

TABLE 10. DATASET INFORMATION – QUEENSLAND IMAGE SAMPLES

Parameter Name	Descriptions
Dataset Name	Highway England Dataset (HighEng)
Dataset Source	England, UK
Number of Item sets	106
Dataset ID	d618ce2e-7d29-4569-97bd-d97bd5831924
Available for API access	Yes
Data Format	CSV

The data available from each datasets are analysed here [Figure – 4].

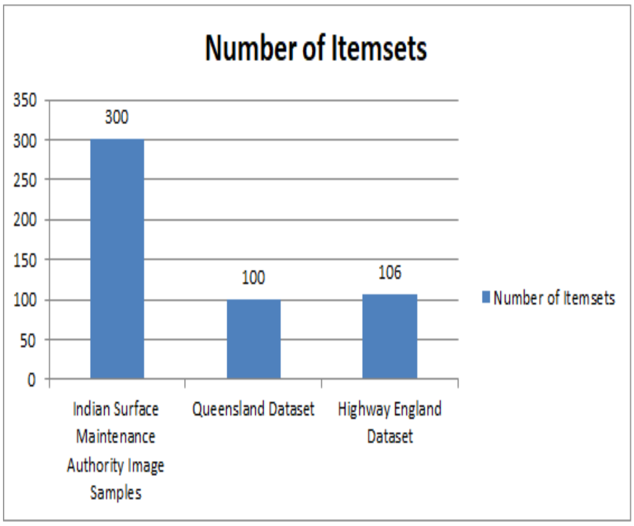

Fig.4 Item Set Analysis for Each Datasets

B. Predictive Classification

Secondly, the predictive classification results are been analysed [Table – 11].

TABLE 11. PREDICTIVE CLASSIFICATION ANALYSIS

Dataset	Number of Instances	Correctly Classified Instances	Correctly Classified Instances (%)	Incorrectly Classified Instances	Incorrectly Classified Instances (%)
ISMAIS	300	300	100	0	0
QesD	100	100	100	0	0
HighEng	106	106	100	0	0

Furthermore, the results of the predicted analysis are also visualized graphically [Figure –5].

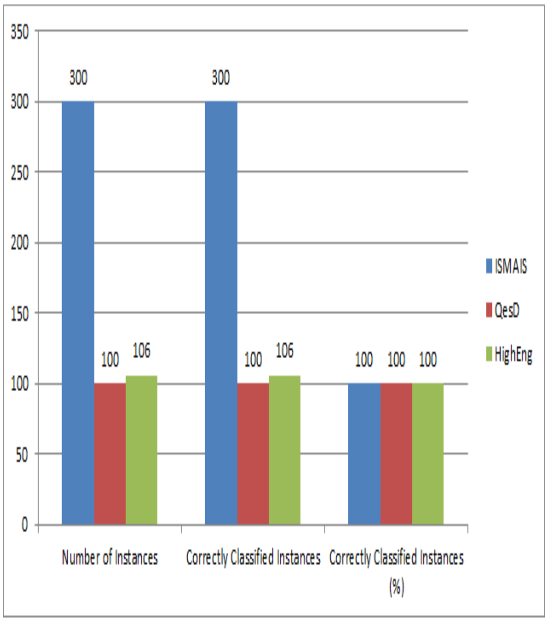

Fig.5 Predictive Analysis Reports

Thus, it is natural to understand that the results of the predictive analysis are highly accurate.

C. Detailed Accuracy Analysis

Third, the stability of the framework is been analysed in terms of statistical accuracy analysis [Table – 12].

TABLE 12. STATISTICAL ACCURACY ANALYSIS

Dataset Name	**Kappa statistic**	**Mean absolute error**	**Root mean squared error**	**Relative absolute error**	**Root relative squared error**
ISMAIS	1	0	0	0	0
QesD	1	0	0	0	0
HighEng	1	0	0	0	0

The results are also been analysed graphically [Figure – 6].

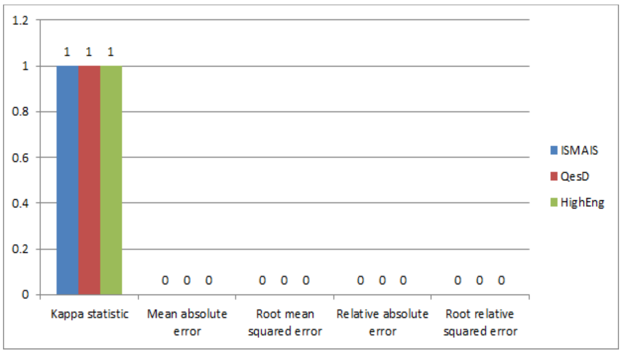

Fig.6 Statistical Accuracy Analysis

Hence, it is natural to understand that the proposed framework is highly stable for any kind of datasets.

D. Confusion Matrix Analysis

Forth, the classification results are been analysed for all three datasets [Table – 13].

TABLE 13. CLASSIFICATION ANALYSIS

Classes	**Classified as Class – A**	**Classified as Class – B**	**Classified as Class – C**
Actual Class – A	40	0	0
Actual Class – B	0	244	0
Actual Class – C	0	0	222

The results are analysed graphically [Figure – 7].

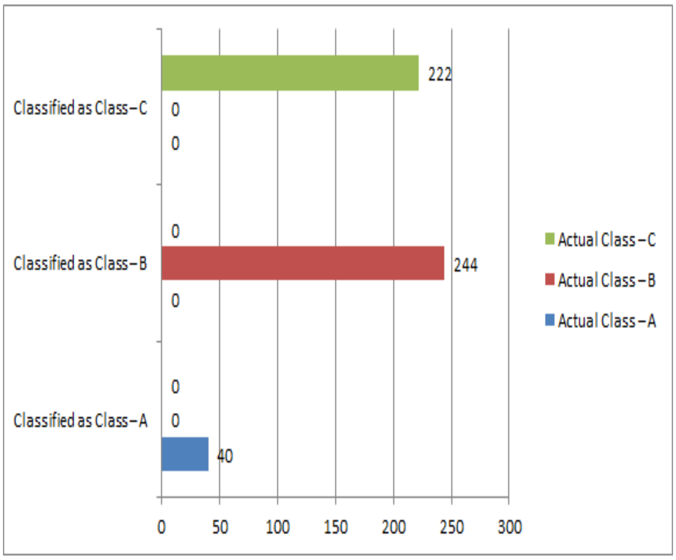

Fig.7 Confusion Matrix Analysis

Hence, it is natural to understand that the high accuracy of this framework is to reduce the confusion values or incorrect classifications.

E. Weather Information Results

Next, the weather information component is furnished here for India, AUS and UK [Table – 14].

TABLE 14. WEATHER INFORMATION RESULTS

RECORD.ID	802	803	600
LONGITUDE	78.47	-114.02	-1.9
LATITUDE	17.36	50.94	52.48
CLOUD	scattered clouds	broken clouds	light snow
CURRECT.TEMP (Kelvin)	295.34	255.59	274.38
MAX.TEMP (Kelvin)	297.15	257.15	276.15
MIN.TEMP (Kelvin)	293.15	254.15	273.15
PRESSURE (Pascal)	1017	1021	1017
HUMIDITY	60	65	74
VISIBILITY (Meters)	6000	48279	8000
WIND.SPEED (kmph)	2.1	4.1	4.6
WIND.DIRECTION (Degree)	140	340	310
COUNTRY.CODE	IN	CA	GB
SUNRISE.TIME (HH:MM:SS) (IST)	01:16:26	15:03:10	07:39:40
SUNSET.TIME (HH:MM:SS) (IST)	12:44:13	00:37:57	17:04:29
CITY.NAME	Hyderabad	Queensland	Birmingham

F. Scheduler Report

Finally, the repair scheduler report is furnished here for analysis [Table – 15].

TABLE 15. SAMPLE REPAIR SCHEDULE

Def – ID	**Longitude**	**Latitude**	**Number of Objects**	**Width**	**Depth**	**Area**	**Priority**
Def-1	9°32′03″S	26°24′37″W	1	49.83	77.16	8615	Low
Def-2	6°28′50″N	107°14′49″E	1	52.17	100.77	8968	Low
Def-3	30°38′18″S	99°40′04″W	1	64.27	99.67	10734	Low
Def-4	15°42′24″S	133°36′51″W	1	67.07	116.86	13547	Low
Def-5	36°53′03″N	45°32′57″W	1	65.06	269.12	14375	Low
Def-22	59°42′53″S	24°39′52″E	1	71.43	129.6	27669	Mid
Def-23	40°27′31″N	160°33′35″E	1	65.01	69.49	27695	Mid
Def-24	34°46′59″N	4°15′06″W	1	95.91	209.36	28311	Mid
Def-25	46°38′36″S	135°35′40″E	1	83.03	88.39	30912	Mid
Def-142	24°02′40″S	73°21′40″W	1	222.99	321.14	139078	Mid
Def-143	6°00′53″S	76°38′37″W	1	187.72	222.79	142059	High
Def-144	2°04′42″S	5°20′27″W	1	233.66	310.51	145989	High
Def-145	13°36′53″N	154°05′26″W	1	221.3	230.56	146802	High
Def-146	29°39′07″N	124°54′55″E	1	209.87	277.26	147463	High
Def-147	6°21′36″N	29°54′32″W	1	214.08	288.66	148008	High
Def-148	27°07′30″N	111°30′11″W	1	232.86	326.82	148499	High
Def-149	26°42′59″S	68°21′58″E	1	233.27	369.96	149734	High

Def – ID	Longitude	Latitude	Number of Objects	Width	Depth	Area	Priority
Def-150	66°21′11″S	97°01′33″E	1	236.35	398.29	153089	High
Def-151	50°23′17″N	144°56′39″E	1	272.01	422.94	155757	High
Def-152	7°03′22″N	10°47′38″E	1	214.87	292.97	157194	High

Henceforth, the human intervention is required to make the physical repair to be taken place.

6. COMPARATIVE ANALYSIS

In order to understand the improvements of the accuracy in detecting defects and scheduling the repair works, the comparative analysis is carried out in this section. The Comparative analysis is majorly focused on three factors as classification process orientation, accuracy in predictive detection and finally the time complexity.

A. Classification Process Orientation

Firstly, the classification algorithms used for the same purposes are been analysed based on the characteristics of the process and process orientations [Table – 16].

TABLE 16. CLASSIFICATION PROCESS ORIENTATIONS

Algorithm used	Author & Year	Characteristics Extraction	Max / Min Value Analysis	Learning	Probabilistic Function	Statistical Measures	Score (Total)
DecisionStump	AnandKishor Pandey et al. 2016 [21]	Yes (1)	Yes (1)	No (0)	No (0)	Yes (1)	3
ZeroR	Hebert de Oliveira Silva et al. 2017 [22]	Yes (1)	Yes (1)	No (0)	No (0)	Yes (1)	3
NaiveBayes	Juliana Vergara-Reyes et al. 2017 [23]	Yes (1)	No (0)	Yes (1)	No (0)	Yes (1)	3
MultilayerPerceptron	Glorianne Danao et al. 2017 [24]	Yes (1)	No (0)	Yes (1)	Yes (1)	Yes (1)	4
Proposed Algorithm	Suwarna G. et al.	Yes (1)	Yes (1)	Yes (1)	Yes (1)	Yes (1)	5

Hence it is natural to understand that based on the process orientation of the proposed algorithm is scoring the highest rank. The observation is visualized graphically [Figure – 8].

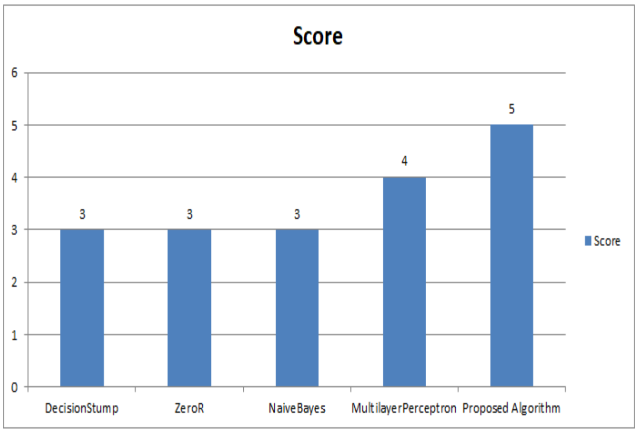

Fig.8Score Comparison

B. Accuracy Analysis

Next the accuracy of the algorithms are been compared in terms of detection or classifications of defects [Table – 17].

TABLE 17. ACCURACY COMPARISONS

Author & Year	Accuracy (%)
AnandKishor Pandey et al. 2016 [21]	92.09
Hebert de Oliveira Silva et al. 2017 [22]	48.22
Juliana Vergara-Reyes et al. 2017 [23]	95.45
GlorianneDanao et al. 2017 [24]	92.09

Suwarna G. et al.	100.00

The obtained accuracies are also visualized graphically [Figure – 9].

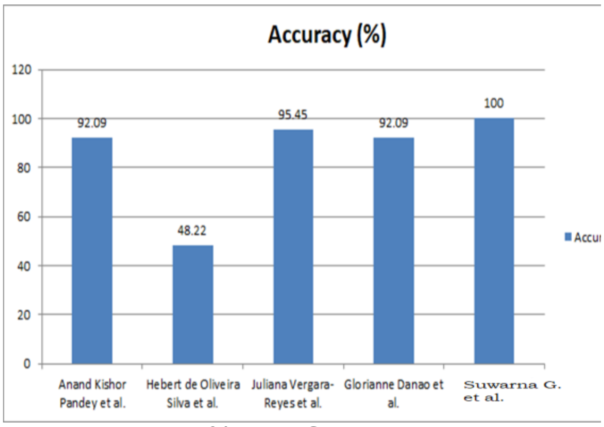

Fig.9Accuracy Comparison

C. *Time Complexity Analysis*

Finally the time complexity analysis is carried out in order to understand the time needed to build the classes and analysed the item sets to be detected [Table – 18].

TABLE 18.TIME COMPLEXITY ANALYSIS

Author & Year	Time (ns)
AnandKishor Pandey et al. 2016 [21]	0
Hebert de Oliveira Silva et al. 2017 [22]	0
Juliana Vergara-Reyes et al. 2017 [23]	0
GlorianneDanao et al. 2017 [24]	12
Suwarna G. et al.	4

The obtained accuracies are also visualized graphically [Figure – 10].

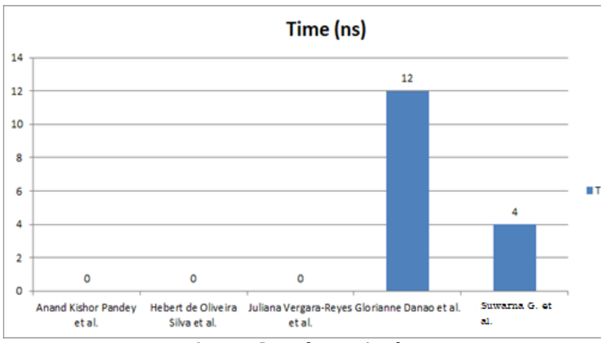

Fig.10Time Complexity Analysis

Hence in the light of the results it is natural to understand that the proposed framework supported by the novel algorithm is highly accurate and comparatively less time complex.

Thus with the result are been analysed, the work furnishes the final conclusion in the next section.

7. CONCLUSION

With the growth of the road transportations, it is important for any building nation to maintain the road conditions in order to cater the best infrastructure and ensure road safety. The road conditions can be maintained by regular repair works and detailed verification time to time. The verification of the road conditions and the repair works can be time consuming due to the weather conditions. The bad weather can influence delay in the repair works and lead to further decay in road surface conditions. Also, the defects on the road surfaces are to be prioritized in order to avoid high maintenance costs. Thus this work proposes a novel framework for predictive detection and automation of road repair schedules for making the most effective road transport system available. The proposed framework can automate the generation of the repair schedule with the weather information on that region in order to decide the start date of the repair workbased on the duration and damage on the road surface. Also, the proposed framework can automate the priority of the defects to be repaired. This work demonstrates a 100% accuracy of the predictive defects detection with comparatively less time complexity. The major outcome of the work is to automate the road surface repair and maintenance works in order to provide a better road for the world.

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ABOUT THE AUTHORS

Authors Profile

Suwarna Gothane is presently working as an Associate Professor in CMR Technical Campus, Hyderabad, Telangana, India. She is pursuing Ph.D. from Sant Gadge Baba Amravati University. She received her M.E (CSE) degree from P.R.M.I.T & R, Amravati in the year 2012. She received B.E. (CSE) degree from H.V.P.M C.O.E & T, in the year 2006. Her areas of interests are Data Mining, Image Processing, Machine learning etc.

Dr. Milindkumar Sarode currently working as HOD. GovernmentPolytechnic, Yavatmal, India. He has completed his Ph. D in Computer Science and Engg. His research area includes Digital Image processing and Algorithms, Distributed System and Data Analysis.

Dr. Vilas M. Thakare currently working as Professor and Head in Computer Science, Faculty of Engineering & Technology, Post Graduate Department of Computer Science, SGBAU. He has completed his Ph.D. in Computer Science. His research interest includes Networking,Mobile Computing, Cyber Security,AI,Robotics.