### DETECTION OF ABNORMALITIES IN THE HUMAN VERTEBRAL COLUMN

A PROJECT REPORT

Submitted by

### ADITYA SINGH SOLANKI [Reg No:RA2011003010183]

**ARPAN GHOSH [Reg No: RA2011003010205]** 

*Under the Guidance of* 

Dr. PADMAPRIYA.G

Assistant Professor, Department of Computing Technologies

in partial fulfillment of the requirements for the degree of

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in

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## DEPARTMENT OF COMPUTING TECHNOLOGIES COLLEGE OF ENGINEERING AND TECHNOLOGY SRM INSTITUTE OF SCIENCE AND TECHNOLOGY KATTANKULATHUR- 603 203 OCT 2023



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CI Delogo Dr.PADMAPRIYA.G

SUPERVISOR

Assistant Professor

Department of Computing Technologies

Dr.K.Vijaya

PANEL HEAD

Assistant Professor

Department of Computing Technologies

Dr. M. PUSHPALATHA HEAD OF THE DEPARTMENT

M. Pushpalatha

Department of Computing Technologies

### OSRM

### Department of Computing Technologies

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Student Names : ARPAN GHOSH, ADITYA SINGH SOLANKI

Registration Number: RA2011003010205, RA2011003010183

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### ARPAN GHOSH [RA2011003010205]

ADITYA SINGH SOLANKI [RA2011003010183]

### **ABSTRACT**

This project aims to detect the presence of abnormalities(fractures) in the vertebral column. The human vertebral column, a fundamental structural component of the spine, plays an integral role in supporting the body and protecting the spinal cord. The integrity of the vertebral column is paramount to overall health, as damage and fractures left untreated can lead to severe complications, impairing standards of living of affected individuals. In the light of vital importance of the vertebral column and the spine, this research project seeks to address the critical issue of detecting and diagnosing fractures within the vertebral column promptly. We have used the L.. R (Logistic Regression) and the S.V.M (Support Vector Machine) algorithm to train our model to perform predictions over the vertebral column image dataset. Result indicates that when training data is used both SVM and LR have no difference in error rate of 0%, whereas in the testing data SVM shows a 0.1% error rate and LR has an error rate of 0.3%. Therefore, SVM is more suitable for detecting spinal fracture. Ultimately, the final aim of our project is to help patients identify and detect potential life threating defects in their vertebral column so that they can receive timely care and can avoid any further resulting complications.

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### LIST OF SYMBOLS AND ABBREVIATIONS

**SVM** Support Vector Machine

LR Logistic Regression

AI/ML Artificial Intelligence/ Machine Learning

MRI Magnetic Resonance Imaging

**CT** Computed Topography

### INTRODUCTION

The vertebral column, often referred to as the spine or backbone, is a marvel of anatomical engineering that holds a central role in the structure and function of the human body. Comprising a series of individual bones known as vertebrae, the vertebral column extends from the base of the skull to the coccyx, forming the axial skeleton. Its significance lies not only in providing structural support to the body but also in safeguarding the delicate and vital spinal cord. This intricate anatomical structure acts as a protective housing for the spinal cord and facilitates a wide range of movements, making it fundamental to human mobility and posture.

The vertebral column is organized into distinct regions, each with its unique characteristics and functions. These regions include the neck (cervical), mid-back lumbar (lower back), and other segments. The cervical region, with its seven vertebrae, allows for the flexibility necessary for head movement and sensory perception, while the thoracic region, housing the rib cage, provides support and protection for vital organs. The lumbar region, consisting of five vertebrae, is responsible for bearing much of the body's weight and facilitating upright posture. The sacral and coccygeal regions form the fused base of the vertebral column and contribute to the overall structural stability.

This intricate bony structure, however, is not without vulnerabilities. Traumatic injuries, degenerative conditions, congenital anomalies, and other medical issues can compromise the integrity of the vertebral column. Left untreated, such abnormalities can lead to a range of complications, including chronic pain, neurological deficits, mobility limitations, and, in severe cases, life-altering consequences.

Given its pivotal role in human health and well-being, preserving the health of the vertebral column and promptly addressing abnormalities is of paramount importance. This research project is dedicated to the early detection of vertebral column abnormalities, with a particular focus on fractures. Through advanced medical imaging techniques, data analysis, and innovative diagnostic tools, our aim is to enhance the accuracy and timeliness of detection, thereby enabling healthcare providers to offer prompt treatment and intervention. By doing so, we aspire to contribute to the well-being of individuals by preventing the progression of vertebral abnormalities and the complications they may entail.

### LITERATURE SURVEY

### 2.1 Challenges in Vertebral Fracture Detection:

Data Augmentation: Vertebral column abnormality datasets can be limited in size. Data augmentation techniques, as such- image rotation, mirroring often are to be employed to enhance the genreal training dataset and improve model generalization.

Cross-Modality Integration: Some research explores the fusion of data from multiple imaging modalities from x-rays to CT scans do provide a more comprehensive assessment of vertebral column health.

Clinical Validation: Ensuring the clinical validity and utility of automated diagnosis systems is essential. Some studies focus on validating the real-world application and impact of these systems in clinical settings

### .

### 2.2 Recent Technological Advancements:

Deep Learning Architectures: Recent years have witnessed the application of the learning architectures in the deep learning field, to help improving the accuracy of vertebral fracture detection.

3D Imaging: The adoption of 3D imaging techniques and volumetric data analysis has shown promise in providing a more comprehensive view of vertebral column abnormalities.

Transfer Learning: The utilization of pre-trained models and transfer learning techniques has accelerated the development of accurate diagnostic systems by leveraging knowledge from related medical imaging tasks.

### 2.3 Machine Learning Algorithms for Vertebral Fracture Detection:

### **ML Model 1 - Support Vector Machine (S.V.M):**

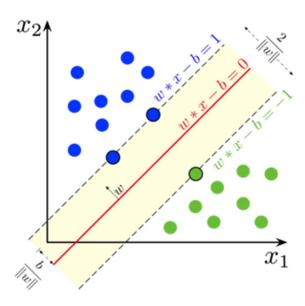


Figure 1: This figure graphical representation of the SVM model we applied.

A Support Vector Machine is formidable technique for machine learning that is used for predictive and classification applications. It is especially attractive for situations in which the objective is to categorize data. based on their features. SVMs are widely acknowledged to functioning effectively in extremely dimensional environments, making them a great pick and valuable tool in various fields, including medical imaging and diagnosis.

A Support Vector Machine functions by identifying the most ideal hyperplane which best discriminates between the difference of class in the dataset.

SVM can be employed for both nonlinear as well as linear systems scenarios. In linear

classification, the SVM seeks a straight-line hyperplane to separate data.

One of the notable advantages of SVM is its robustness in handling datasets with a relatively small number of samples, making it particularly suitable for medical diagnosis where data collection can be limited and valuable. SVMs are also versatile, capable of solving binary and multi-class classification problems.

In the context of our research project aimed at detecting vertebral column abnormalities, SVMs play a pivotal role in the classification of data obtained from medical imaging. By training the SVM on a labeled dataset that includes both normal and abnormal cases, it can learn to distinguish between the two, ultimately assisting in the accurate detection of abnormalities in the vertebral column.

### ML Model 2 - Logistic Regression (L.R):

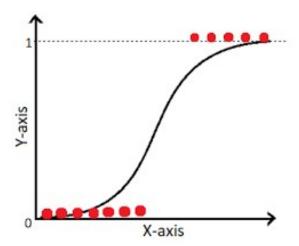


Figure 2: The logistic regression framework is an analytical framework that predicts.

It's an approach that may be applied to multiple class situations as well. Regardless of the name it bears, logistic regression is employed to gauge the chances that any particular input belongs

to one particular group or class.

Logistic regression is well-suited for applications where the goal is to predict a binary outcome, such as whether an email is true or not true, whether a customer will make a purchase, or, in the context of our research project, whether an image from a medical scan contains an abnormality in the vertebral column. Logistic regression is computationally efficient, interpretable, and can be a valuable tool for making binary classifications based on a set of features.

By training the logistic regression model on labeled data, it can learn to classify medical vertebral column images or as normal or abnormal based on the extracted features, aiding in the early detection of abnormalities.

### **Differences between both the Models:**

Table 1 : Comparison a Support Vector Machine vs. a Logistic Regression Model.

Aspect	S.V.M(Support Vector Machine)	LR(Logistic Regression)		
Type of Algorithm	Classification and Regression	Classification		
Classification	Suitable for binary and multiclass classification problems.	Primarily used for binary classification, but can be extended for multiclass.		
Output Interpretation	The distance to the decision border shows class probability, and the hyperplane is determined to optimize the margin between classes.	to directly model the		
Kernel Functions	To handle linear and non-linear data, several kernel functions (such as polynomial, linear, or radial foundation function) can be used.	It can only be used with simple models and is harder to implement with others.		
Interpretability	May be less interpretable due to complex decision boundaries in high-dimensional spaces.	More interpretable as it provides coefficient values for each feature, indicating their impact on the output.		
Robustness Robust in handling datasets with Suitable for da				

	relatively small sample sizes.	various sizes, but may		
		require more data for stable		
		performance.		
Complexity	When dealing with massive data sets or sophisticated kernel functions, a Support Vector Machine can be extremely CPU-intensive.	Generally, computationally efficient, making it more suitable for simpler tasks.		
Use Cases	Effective in scenarios where maximizing the margin between classes is critical (e.g., image classification, bioinformatics).	Suitable for applications requiring modeling the likelihood of belonging to a class (including identifying fraudulent transactions, healthcare evaluation).		

### 2.4 Data Preprocessing Techniques:

Data Preprocessing is vital to boosting the level of detail of health-related imagery for accurate fracture detection.

Common techniques include noise reduction, image registration, and contrast enhancement.

Standardization of data formats and annotation practices is vital for consistency in training datasets.

### 2.5 Clinical Impact of Automated Diagnosis:

Automated diagnosis systems significantly reduce diagnosis time, allowing for prompt patient care decisions.

Increased accuracy in vertebral fracture detection enhances patient outcomes by enabling early interventions.

Radiologists can use automated systems as a valuable second opinion, reducing the chances of misdiagnosis.

### 2.6 Future Directions:

Real-time Telemedicine: The integration of automated vertebral fracture detection systems into telemedicine platforms holds the potential to enable remote real-time diagnosis and consultation. Multimodal Integration: Studies in the future may look into merging several diagnostics methodologies, such as health imaging alongside patient data and clinical history for enhanced diagnostic accuracy.

Patient-Centered Solutions: The development of patient-centered tools that empower individuals to monitor and assess their vertebral column health is an emerging area of interest.

### PROPOSED METHODOLOGY

### 3.1 Data Collection

Data Collection for AI is crucial because the quality and quantity of data directly impact the performance and accuracy of machine learning models. Gathering high-quality data helps in identifying patterns and trends, enabling AI systems to make predictions and improve decision-making processes. Data privacy is a major concern when collecting data for AI applications. Organizations must adhere to regulations like GDPR or HIPAA to ensure the data they collect is handled ethically and securely. Biases in the collected data can lead to skewed or inaccurate AI models. To avoid this, organizations must Make certain that the data is true to the entire population and not just a specific segment.

Data Collection for AI should focus on gathering complete, relevant, and up-to-date data. Incomplete or outdated data may lead to incorrect predictions or decision-making. Prepackaged data involves purchasing third-party data, which can save time but may require customizations, API integrations, and additional resources to make it suitable for AI applications. We gathered a diverse dataset of medical images of the vertebral column, including both normal and fracture cases, from open source Kaggle repository.

### 3.2 Data Preprocessing

Importing libraries is the first step in machine learning data preparation. A library is just a collection of functions that may be called and utilized within an algorithm. There are several libraries available in various programming languages. The next critical step is to load the data

that will be used by the machine learning algorithm. This is the most crucial phase in machine learning preprocessing. The collected data will be imported for further analysis.

It is critical to check for noisy or missing material once the data has been loaded. Scaling is a strategy for reducing the range of data values. Data may be scaled using Rescaling and Standardization. The final stage is to divide the data into three groups: training, validating, and evaluating.

### 3.3 Feature Extraction

Various methods come into play here. The method of principal component analysis (PCA) was used to reduce dimensionality and extract significant characteristics from medical imagery, with an emphasis on texture, form, and intensity-based facets.

**3.4 Model Selection** A Support Vector Machine, also called an SVM, is an intricate where the objective is to categorize data based on its characteristics. SVMs are well-known for their performance in high-dimensional environments, making them an invaluable tool in a variety of domains, including medical imaging and diagnostics.

The SVM technique works by identifying the optimum hyperplane for discriminating between distinct classes in the dataset.

Such as whether is true or not, if a consumer would make a purchase, or, in the context of our study project, whether a picture from a medical scan has a spinal column anomaly.

Logistic regression may be used as one of the categorization approaches in our study project to identify the existence of vertebral column anomalies.

SVM training: In our initial step, we will import the libraries that are needed for the SVM implementation in our project. The iris dataset, that can be obtainable via the load iris() function,

will be used in the subsequent stage of SVM implementation in Python. In this study, we will just consider petal length and breadth. To ensure robust performance, I trained the SVM model with the labeled dataset, modifying hyperparameters and utilizing k-fold cross-validation.

Training Logistic Regression: First, we must choose which columns to include. Using raw\_data.columns, you may get a list of the Data Frame's columns. Logistic Regression was used, and the model was trained using the training instances.

Metrics of Performance: It generates two labels as output, like No or Yes, 0 or 1, It's true or not and more and more. To create an accuracy metric, we may use a loop to compare ground truth and forecasted values, or we can utilize the program scikit module. Comparison of both the models: The performance (testing score accuracy) of both the models were compared side by side on the basis of how accurately they were able to make predictions.

Visualization and plotting of results: The Confusion Matrices, side by side Bar Graph and Pie Charts to compare the accuracy of both the models were plotted and visualized.

Challenges Faced: Acknowledged challenges related to image quality variations and computational requirements. Acknowledged challenges relating to the limitation of medical dataset access. There various challenges from learning new AI models to managing frequent meetups with project partner who has different schedules and finding a dataset to train the models from, but with enough dedication and problem solving we were able to solve all the challenges presented to us in the best possible way without going out of scope of the project.

Future Directions: Plan to work with actual spine vertebral column images (DICOM format) instead of just the cross section and plan to include more classes instead of just a simple binary classification for our next project.

### 3.5 Architecture Diagram

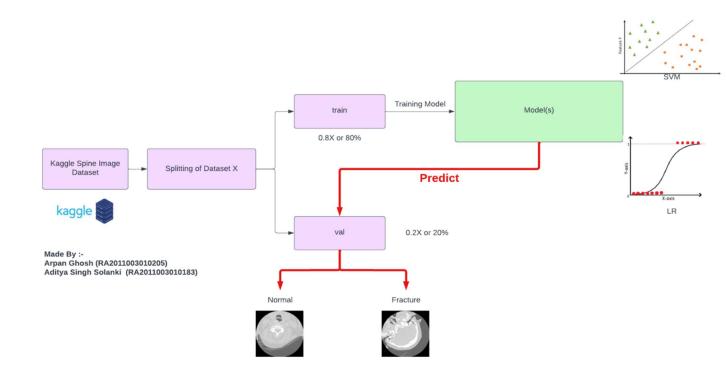


Figure 3: The Architecture Diagram for the project which demonstrates how the models predict the test dataset images into two classes Normal(0) and Fracture(1).

First the vertebral column cross-section image dataset is loaded from Kaggle repository. Next, we split the entire dataset into training and testing directories. Training directory has 0.8 times (or 80%) of the total images of the dataset and the remaining 20% of the images go for testing the model. Next the models are trained using the training examples. The two models being SVM and Logistic Regression. Now this trained model makes predictions using the unseen examples present in the test dataset and it performs binary classification of the images in test (Normal -0 and Fracture -1).

### 3.6 Algorithm and Implementation

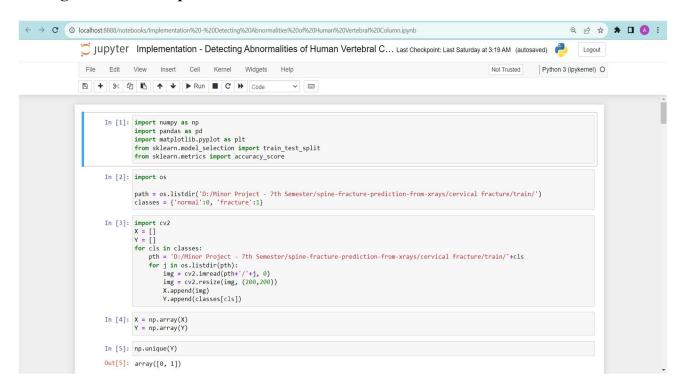


Figure 4: Implementation carried out in the Jupyter IDE. Resizing being carried out on images for uniformity (200 X 200).

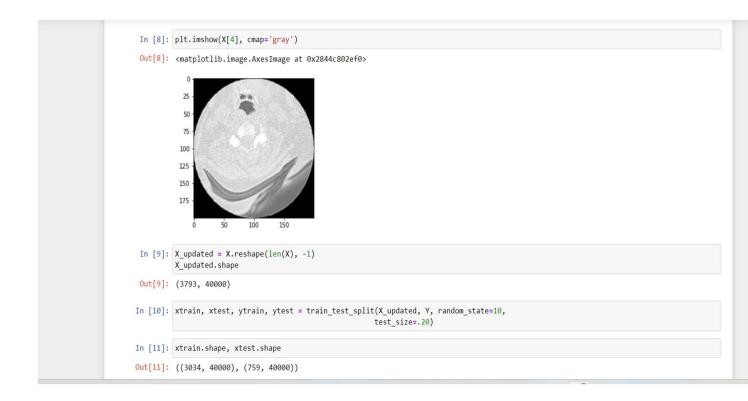


Figure 5: Implementation carried out in the Jupyter IDE. This image shows the dimensionality of the image dataset.

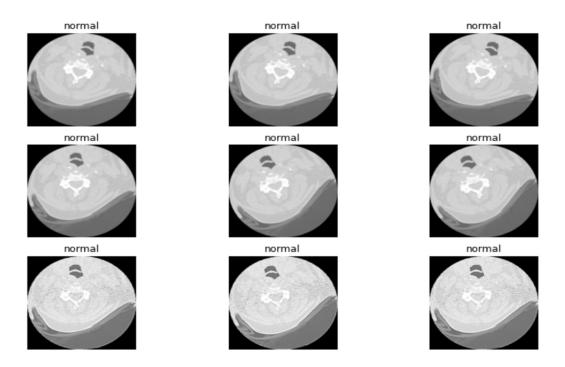


Figure 6: Pediction carried out by the model on the test dataset.

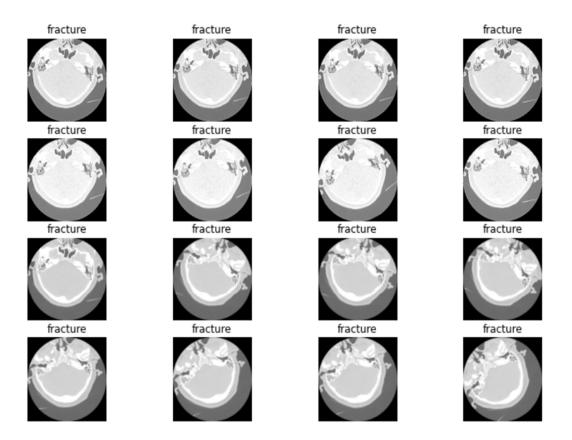


Figure 7: Pediction carried out by the model on the test dataset.

```
In [18]: print("Training Score:", lg.score(pca_train, ytrain))
    print("Testing Score:", lg.score(pca_test, ytest))

    Training Score: 1.0
    Testing Score: 0.997364953886693

In [19]: print("Training Score:", sv.score(pca_train, ytrain))
    print("Testing Score:", sv.score(pca_test, ytest))

    Training Score: 1.0
    Testing Score: 0.9986824769433466
```

Figure 8: The Training and Testing scores of the Logistic Regression and SVM Models. As it can be observed here that SVM performs significantly better among the models.

```
Logistic Regression -- 0.997364953886693
SVM -- 0.9986824769433466
```

### **Accuracy Comparison of both the models**

Table 2: Accuracy comparison of both the ML Models.

Sno.	ML Model	Accuracy	Error
1.	Support Vector	0.9986824769433466	0.0013175230566534
	Machine		
2.	Logistic	0.997364953886693	0.002635046113307
	Regression		

### **RESULTS**

### Plotting and Visualization

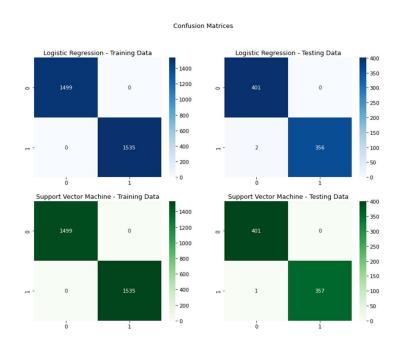


Figure 9: Confusion matrix to find out FP (false positive), FN(false negative), TP(true positive), TP(true negative).

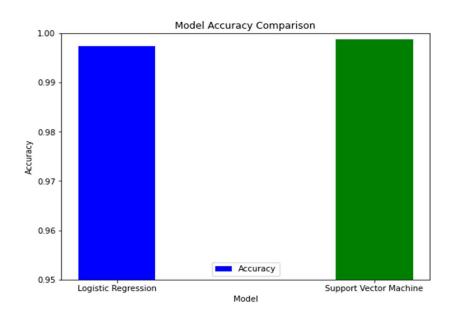


Figure 10: The chart above shows the comparison between the LR and SVM test dataset using a bar chart for visualization. As observed here that SVM performs slightly better among the two models.



Figure 11: The chart above shows the comparison between the LR and SVM test dataset using a pie chart for visualization.

### CONCLUSION

- 1. We were successfully able to train both our SVM and Logistic Regression models successfully using the training data.
- 2. The models were then successfully able to classify almost all the data points/images correctly as either fracture 1 or normal 0 using the testing image dataset where it performs predictions on completely unseen data.
- 3. It was observed that for our given dataset, both the models performed exceptionally well but SVM (99.86%) performed slightly better than Logistic Regression (99.73%).
- 4. The Confusion Matrixes, Bar Graph and Pie Charts were plotted for Visualization.
- 5. So, we were able to address our final objective of classifying and detecting abnormalities in the human vertebral column using the proposed models with satisfactory results.

### **FUTURE SCOPE**

In the future the plan is to extend the same idea by using special DICOM Medical Images instead of just .png images.

The plan is to use normal side-view images of the spine/ vertebral column as we would normally imagine instead of cross-sectional images.

Instead of just performing a binary classification, the plan is to perform a multi-class classification if the extension of the project is carried out.

The plan is to detect a wide array and range of abnormalities in the vertebral column instead of just 0 (Normal) and 1 (Fracture).

The plan is to use different algorithms in the extension instead of just the simple classification algorithms/models (S.V.M and L.R) used in this minor project.

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1	Name of the Candidates (IN BLOCKLETTERS)	Aditya Singh Solanki Arpan Ghosh
2	Address of the Candidates	G-7, Newtown, Rajarhat, Kolkata, West Bengal, 700156.  D-2, Vaibhava Spoorthi, 15th Cross, Kuvempu Road,
3	Registration Number	Vignanagar, Bengaluru - 560075 RA2011003010183 RA2011003010205
4	Date of Birth	11th September 2002 8th May 2002
5	Department	Computer Science and Engineering
6	Faculty	Engineering and Technology, School of Computing
7	Title of the Dissertation/Project	Detection of Abnormalities in the Human Vertebral Column
8	Whether the above project /dissertation is done by	Individual or group  (Strike whichever is not applicable)  a) If the project/ dissertation is done in group, then how many students together completed the project : 2  b) Mention the Name & Register number of other candidates  Aditya Singh Solanki (RA2011003010183)  Arpan Ghosh (RA2011003010205)
9	Name and address of the Supervisor / Guide	SRM Nagar, Kattanakulathur – 603203, Chengalpattu District, Tamil Nadu  Mail ID: padmaprg   @srmist.edu.in
10	Name and address of Co-Supervisor / Co- Guide (if any)	Mobile Number: 9095274310
		Mail ID: Mobile Number:

11	Software Used	Turnitin				
12	Date of Verification	3/11/2023				
13	Plagiarism Details: (to attach the final r	report from the software)				
hapter	Title of the Chapter	Percentage of similarity index (including self citation)	Percentage of similarity index (Excluding self-citation)	% of plagiarism after excluding Quotes, Bibliography, etc.,		
1	Introduction	<1%	0	0		
2	Literature Review	0	0	0		
3	Proposed Methodology	0	0	0		
4	Results	0	0	0		
5	Conclusion	0	0	0		
6	Future Scope	0	0	0		
7	References	0	0	0		
8						
9						
10						
	Appendices					

Aditya.S

Signature of the Candidates

Name & Signature of the Super Sor Evide

Name & Signature of the Co-Supervisor/Co-Guide

M. Pushpalatta

Name & Signature of the HOD



SRM INSTITUTE OF SCIENCE & TECHNOLOGY							
	Department	t of Computing Technologies,		nd Technology			
		Final Year Minor Project/Int					
Dograo Pro	ogramme B.Tech   B.Arch   B.	Academic Ye		(Multi selection permitted)			
	ogramme b.lecn   b.Arch   b. Campus KTR   RMP   VDP	INCR	Bio Project York (		<del>                                     </del>	+	
BEMARKS, If any:	Campus KTR   Nill   VDI	Batch ID: B249	Chemical Project	Industry Project / Internship	<del>                                     </del>	+	
TILITINO, II any .		Batch ID: B249	Chemical Project	Industry Project / Internship Software Project	<u> </u>		
n e e e e e e e e e e e e e e e e e e e			FTOJECC	SORWAIE PTOJECC	<del>                                     </del>	+	
			Experimental / Testing Project				
	1	2	3	4	5	6	
Name of the students	Aditya Singh Solanki	Arpan Ghosh					
Registration Number	RA2011003010183	RA2011003010205					
	1	2	3	4	5	6	
i	-l	's Gs sishing short					
Q1 What kind of dataset is used for		doesn't fit within the given s	space, you may eitner me	rge the cells of attach sepa	rate sneet		
_ ·	or the						
project?	The project uses an imag	e dataset Containing cross -	sectional images of the h	uman vertehral column			
	The project uses an imag	the project uses an image dataset Containing cross - sectional images of the human vertebral column.					
Q2 How big is the dataset?							
	The dataset consistes of	roughly about 3000 images,	80% of which have been	used to train the model and	remaining 20% to to	est the model.	
		1					
Q3 What are the models used?							
	The models used in the p	project are the Support Vect	or Machine (S.V.M ) and t	he Logistic Regression (L.R).			
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04.4						+	
Q4 Any challenges faced?							
	Finding the right kind of	dataset to train our models of	on was a hig challenge.				
	Finding the right time of	dataset to train our moders	OII Was a DIE CHAILCHEC				
Q5 Why have you used SVM and LR	2					1	
<b>45, ,</b>							
Because SVM and LR are suitable and excellent models for binary classificaton tasks involving image datasets.							