Dectection of Abnormalities in the Human Vertebral Column

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***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 damages and fractures left untreated can lead to severe complications, impairing the quality of life for affected individuals. In light of the 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 Logistic Regression (LR) and the Support Vector Machine (SVM) algorithms to train our model to perform the predictions over the vertebral column image dataset.**

INTRODUCTION

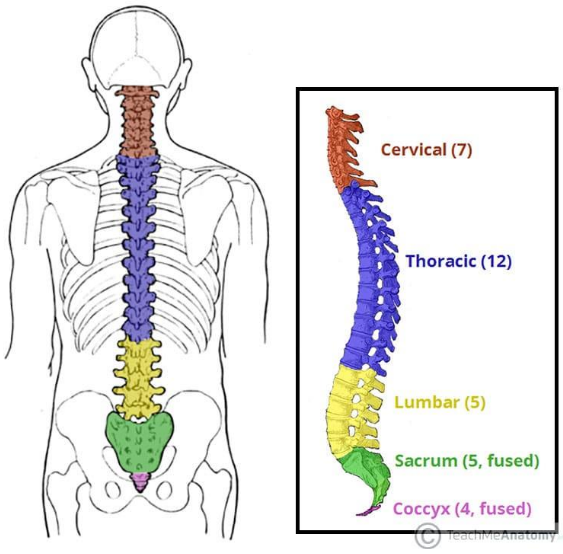
Vertebral Column:

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 cervical (neck), thoracic (mid-back), lumbar (lower-back), sacral (sacrum) and coccygeal (coccyx) 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

Vertebral Fracture Detection Data Augmentation Vertebral column abnormality datasets can be limited in size. Data augmentation techniques, such as image rotation and mirroring, are often employed to enhance the training dataset and improve model generalization. Cross-Modality Integration**:** Some research explores the fusion of data from multiple imaging modalities (e.g., X-rays, CT scans, MRIs) to 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. Recent Technological Advancements in the field are Deep Learning Architectures Recent years have witnessed the application of deep learning architectures, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), in 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.

Machine Learning Algorithms for Vertebral Fracture Detection:

SVM (Support Vector Machine) and Logistic Regression are widely used algorithms for vertebral fracture detection. Decision Trees and Random Forests have also shown promise in automating the diagnosis of vertebral column abnormalities. Deep Learning techniques, particularly Convolutional Neural Networks (CNNs), are gaining traction for their ability to learn intricate patterns in medical images. Data preprocessing plays a crucial role in improving the quality of medical images 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.

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.

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: Future research may explore the integration of multiple diagnostic modalities, such as combining medical imaging with patient data and clinical history for enhanced diagnostic accuracy.

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

Challenges in Vertebral Fracture Detection:

Detecting vertebral column abnormalities is a complex task that presents several challenges. One major challenge is the variability in the appearance of fractures and abnormalities across different patients. The shape, size, and location of abnormalities can vary significantly, making it crucial to develop robust and adaptable detection algorithms. Moreover, the presence of noise and artifacts in medical images can further complicate the diagnostic process. Researchers are actively working on developing algorithms that are resilient to such variations and can provide accurate results across a wide range of cases.

Interpretable AI Models:

Interpretable artificial intelligence models are gaining importance in the field of vertebral fracture detection. As these models become increasingly sophisticated, there is a growing need to understand how they arrive at their diagnostic decisions. Interpretability is vital not only for ensuring the trust of medical professionals but also for complying with regulatory requirements. Researchers are exploring methods to make AI models more transparent, allowing radiologists and physicians to comprehend and trust the decisions made by these systems.

Ethical Considerations and Data Privacy:

The use of AI in healthcare, including vertebral fracture detection, raises important ethical and privacy considerations. Ensuring patient data security, informed consent, and compliance with regulatory standards such as HIPAA (Health Insurance Portability and Accountability Act) is paramount. Researchers and developers are working on developing secure and privacy-preserving AI solutions to address these concerns while maximizing the benefits of automated diagnosis.

Quantitative Assessment and Progress Monitoring:

In addition to detecting abnormalities, there is a growing interest in providing quantitative assessments of vertebral column health. AI systems can not only identify fractures but also measure their severity, progression, and impact on a patient's overall health. This quantitative approach enables healthcare professionals to better monitor the evolution of vertebral column conditions over time and tailor treatment plans accordingly.

Collaboration with Medical Experts:

Collaboration between data scientists, machine learning engineers, and medical professionals is essential for the success of automated diagnosis systems. The input of radiologists and spine specialists is invaluable in fine-tuning algorithms, validating results, and ensuring that AI systems align with the clinical workflow. These partnerships help bridge the gap between AI research and real-world medical practice.

Addressing Data Imbalance and Rare Cases:

In medical imaging, data imbalance can be a significant issue, as certain vertebral abnormalities are rare compared to more common conditions. Researchers are actively working on techniques to handle imbalanced datasets and improve the detection of rare cases. This is critical for comprehensive and inclusive automated diagnosis systems.

Regulatory Approvals and Standardization:

For AI-based vertebral fracture detection systems to be widely adopted, they need to go through rigorous regulatory approval processes. Regulatory bodies, such as the FDA in the United States, play a vital role in ensuring the safety and efficacy of these systems. Additionally, standardization of evaluation metrics and practices is essential for comparing and benchmarking different algorithms and models effectively.

Long-term Monitoring and Rehabilitation Support:

While the focus has primarily been on the detection of vertebral column abnormalities, there is growing interest in AI applications for long-term monitoring and rehabilitation support. These systems can aid in tracking a patient's progress, suggesting personalized exercises, and facilitating tele-rehabilitation programs.

These are some of the emerging trends and considerations in the field of vertebral column abnormality detection, showcasing the ongoing efforts to improve the accuracy, accessibility, and utility of automated diagnosis systems in healthcare.

ML Models:

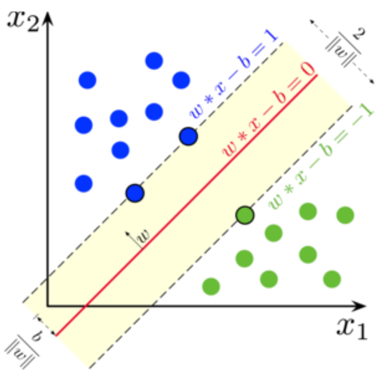
1. Support Vector Machine (S.V.M)

A Support Vector Machine (SVM) is a powerful machine learning algorithm used for classification and regression tasks. It is particularly well-suited for applications where the goal is to separate data into different categories based on their features. SVMs are known for their effectiveness in high-dimensional spaces, making them a valuable tool in various fields, including medical imaging and diagnosis. SVM operates by finding the optimal hyperplane that best discriminates between different classes in the dataset. This hyperplane is chosen in such a way that it maximizesthe margin, which is the distance between the hyperplane and the nearest data points from each class. These nearest data points are known as support vectors, hence the name "Support Vector Machine." The idea behind this approach is to create a decision boundary that is as far away from the data points as possible, allowing for better generalization and classification accuracy. SVM can be used in both linear and non-linear scenarios. In linear classification, the SVM seeks a straight-line hyperplane to separate data, while in non-linear cases, it can employ various kernel functions to map the data into a higher dimensional space, making it possible to find non-linear decision boundaries. 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.

In a binary classification problem, the SVM finds a hyperplane that best separates the data into two classes. The equation for this hyperplane can be represented as:

$$f(x) = \text{sign}(W \bullet X + b)$$



1. f(x) is the decision function that predicts the class label (either +1 or -1).
2. X is the input feature vector.
3. W is the weight vector (perpendicular to the hyperplane).
4. b is the bias or intercept term.
5. • represents the dot product between W and X.

The goal of the SVM is to find the optimal values of W and b that maximize the margin between the two classes while minimizing the classification error. This can be formulated as an optimization problem with constraints, often solved using techniques like quadratic programming.

SVM introduces constraints to ensure that data points are correctly classified and that the margin is maximized. These constraints can be written as follows:

For positive class (y = +1):

$$W \bullet X + b \geqslant 1$$

For negative class (y = -1):

$$W \bullet X + b \leqslant -1$$

Here, "y" represents the class label, and we want to ensure that data points from the positive class are on or above the hyperplane ($W \bullet X + b \geqslant 1$) and data points from the negative class are on or below the hyperplane ($W \bullet X + b \leqslant -1$).

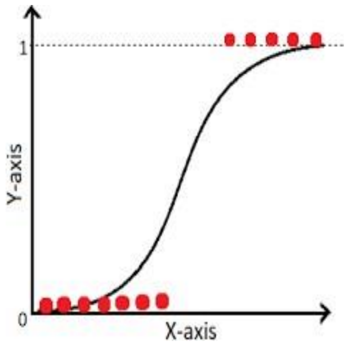
2. Logistic Regression (L.R)

Logistic Regression is a fundamental machine learning algorithm used primarily for binary classification tasks. It's an approach that can also be extended to multiclassclassification problems. Despite its name, logistic regression is not used for regression tasks but for estimating the probability that a given input belongs to a particular category or class. The core idea behind logistic regression is to model the relationship between the independent variables (features) and a binary dependent variable (the target variable) using the logistic function. This function produces an S-shaped curve, which can be interpreted as the probability that the input belongs to a specific class. The logistic function transforms any real-valued number into a value between 0 and 1, which can be interpreted as a probability.

In the context of binary classification, logistic regression calculates the probability that an input belongs to the positive class. If this probability is greater than a chosen threshold (typically 0.5), the input is classified as the positive class; otherwise, it's classified as the negative class.

Logistic regression is well-suited for applications where the goal is to predict a binary outcome, such as whether an email is spam or not spam, 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.

In the context of our research project, logistic regression may be employed as one of the classification methods to assess the presence of vertebral column abnormalities. 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.



Logistic Function (Sigmoid Function):

The logistic function is an S-shaped curve that maps any real-valued number to a value between 0 and 1. It is defined as:

$\sigma(z) = 1 / (1 + e^{(-z)})$

$\sigma(z)$ represents the probability of the positive class (y = 1).

z is a linear combination of the input features:

z = b0 + b1 * x1 + b2 * x2 + ... + bn * xn

Where x1, x2, ..., xn are the input features, and b0, b1, b2, ..., bn are the model parameters or coefficients.

Odds Ratio:

The odds ratio is defined as the ratio of the probability of the event happening to the probability of the event not happening. In logistic regression, the odds ratio is calculated as:

Odds(y = 1 | X) = P(y = 1 | X) / (1 - P(y = 1 | X))

Log-Odds (Logit):

The log-odds, also known as the logit, is the natural logarithm of the odds ratio. It's used to transform the probability estimate into a linear equation. The logit function is given by:

logit(P(y = 1 | X)) = ln(Odds(y = 1 | X)) = b0 + b1 * x1 + b2 * x2 + ... + bn * xn

This equation can be written in a more compact form as:

logit(P(y = 1 | X)) = Σ(bi * xi) for i = 0 to n

Maximum Likelihood Estimation:

The logistic regression model is trained by finding the values of the coefficients (b0, b1, b2, ..., bn) that maximize the likelihood of the observed data. This is typically done using maximum likelihood estimation (MLE).

Decision Boundary:

In binary classification, a decision boundary is chosen to separate the two classes. The decision boundary is determined by the values of the coefficients and input features. For example, if the decision boundary is defined as:

logit(P(y = 1 | X)) = 0

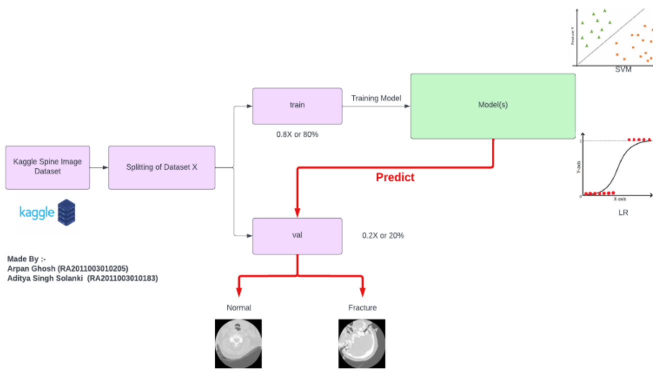
Then, you can solve for X to find the boundary equation.

Differences between both the Algorithms:

Aspect	**Support Vector Machine**	**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 to multiclass.
Kernel Functions	Can employ various kernel functions (e.g., linear, polynomial, radial basis function) to handle linear and non-linear data.	Typically applied to linearly separable data, but it can be extended to non- linear data using feature engineering.
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 relatively small sample sizes.	Suitable for datasets of various sizes, but may require more data for stable performance.
Complexity	SVM can be computationally	Generally, computationally

	intensive, especially when dealing with large datasets or complex kernel functions.	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 where modeling the probability of belonging to a class is important (e.g., fraud detection, medical diagnosis).

ARCHITECTURE DIAGRAM



Explanation of the Architecture Diagram:
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 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).

IMPLEMENTATION

The steps we have followed in our implementation stage can be briefly summarized as: -

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 ensure that the data is representative of 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.

Data Preprocessing: The foremost step of data preprocessing in machine learning includes importing some libraries. A library is basically a set of functions that can be called and used in the algorithm. There are many libraries available in different programming languages. The next important step is to load the data which has to be used in the machine learning algorithm. This is the most important machine learning preprocessing step. Collected data is to be imported for further assessment.Once the data is loaded, checking for noisy or missing content is important. Scaling is a technique that can convert data values into shorter ranges. Rescaling and Standardization can be used for scaling the data. The final step is to distribute data in three different sets, namely Training, validating, evaluation. The training set is to train the data. The validation set is to validate the data The evaluation set is to evaluate the data.

Feature Extraction: In real-world machine learning problems, there are often too many factors (features) on the basis of which the final prediction is done. The higher the number of features, the harder it gets to visualize the training set and then work on it. Sometimes, many of these features are correlated or redundant. This is where dimensionality reduction algorithms come into play. Used Principal Component Analysis (PCA) for dimensionality reduction and to extract relevant features from medical images, focusing on texture, shape, and intensity-based features.

Model Selection: A Support Vector Machine (SVM) is a powerful machine learning algorithm used for classification and regression tasks. It is particularly well-suited for applications where the goal is to separate data into different categories based on their features. SVMs are known for their effectiveness in high-dimensional spaces, making them a valuable tool in various fields, including medical imaging and diagnosis. SVM operates by finding the optimal hyperplane that best discriminates between different classes in the dataset. This hyperplane is chosen in such a way that it maximizes the margin, which is the distance between the hyperplane and the nearest data points from each class. These nearest data points are known as support vectors, hence the name "Support Vector Machine." Logistic regression is well-suited for applications where the goal is to predict a binary outcome, such as whether an email is spam or not spam, 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.

In the context of our research project, logistic regression may be employed as one of the classification methods to assess the presence of vertebral column abnormalities.

Training SVM: In the first step, we will import the important libraries that we will be using in the implementation of SVM in our project . In the second step of implementation of SVM in Python, we will use the iris dataset that is available with the load iris() method. We will only make use of the petal length and width in this analysis. Trained the SVM model with the labeled dataset, optimizing hyperparameters, and using k-fold cross-validation to ensure robust performance.

Training Logistic Regression: The first thing we need to do is split our data into an x-array (which contains the data that we will use to make predictions) and a y-array (which contains the data that we are trying to predict. First, we should decide which columns to include. You can generate a list of the Data Frame's columns using raw_data.columns. Employed Logistic Regression and trained the model using the training examples.

Performance Metrics: In a classification problem, the category or classes of data is identified based on training data. The model learns from the given dataset and then classifies the new data into classes or groups based on the training. It predicts class labels as the output, such as Yes or No, 0 or 1, Spam or Not Spam, etc. To implement an accuracy metric, we can compare ground truth and predicted values in a loop, or we can also use the scikit-learn module for this.

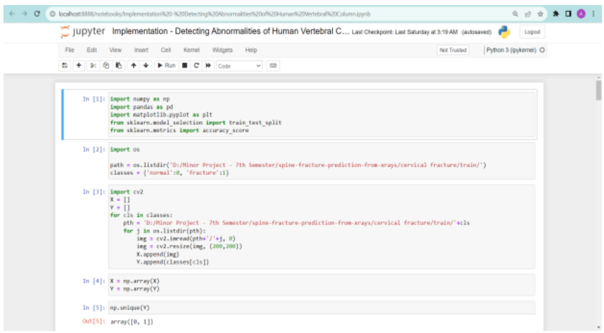
Comparison of both the models: The performance (testing score accuracy) of both the models were compared side by side on the basis of how accurately they were able to make predictions.

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.

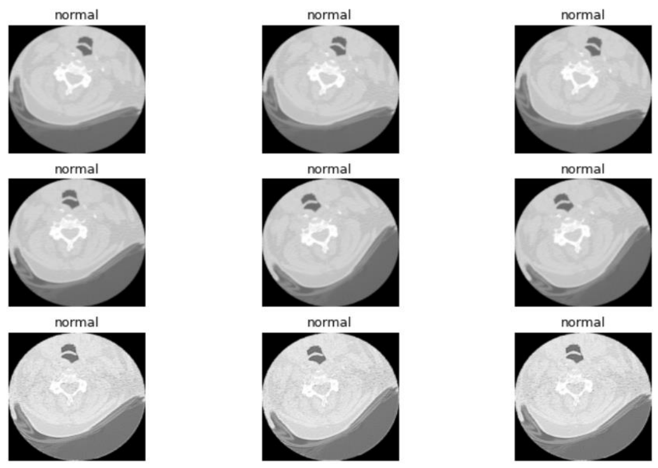
Challenges Faced: Acknowledged challenges related to image quality variations and computational requirements. Acknowledged challenges relating to the limitation of medical dataset access. There various challenges from learning new AI models to managing frequent meetups with project partner who has different 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.

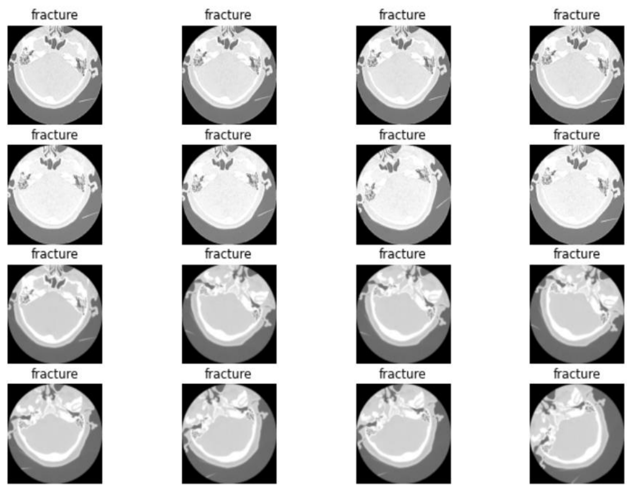
Future Directions: Plan to work with actual spine vertebral column images (DICOM format) instead of just the cross section and plan to include more classes instead of just a simple binary classification for our next project.

Code and Jupyter Environment:



Detecting the output labels (performing predictions) on the test images:





Testing Scores of both the models:

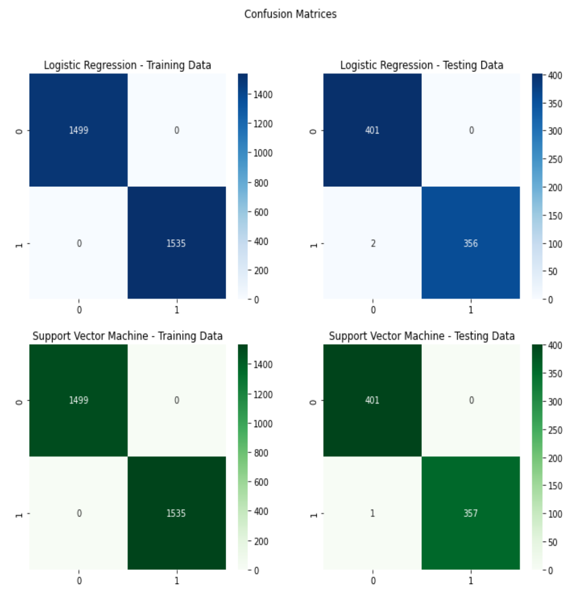
```
In [18]: print("Training Score:", lg.score(pca_train, ytr
         print("Testing Score:", lg.score(pca_test, ytest

         Training Score: 1.0
         Testing Score: 0.997364953886693

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

         Training Score: 1.0
         Testing Score: 0.9986824769433466
```

Logistic Regression -- 0.997364953886693

SVM -- 0.9986824769433466

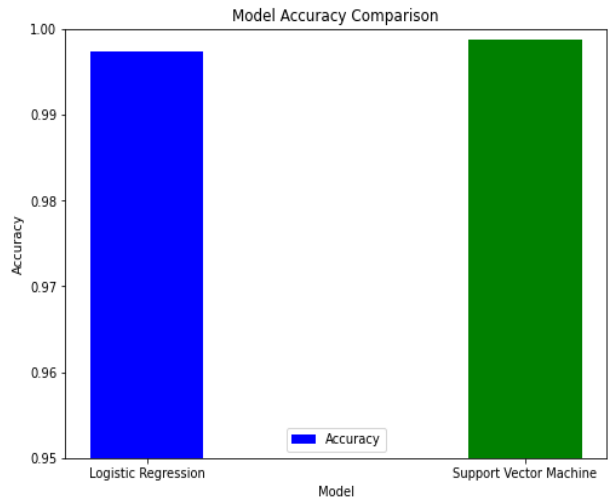
PLOTTING AND VISUALIZATION

➢ **Confusion Matrix: -**



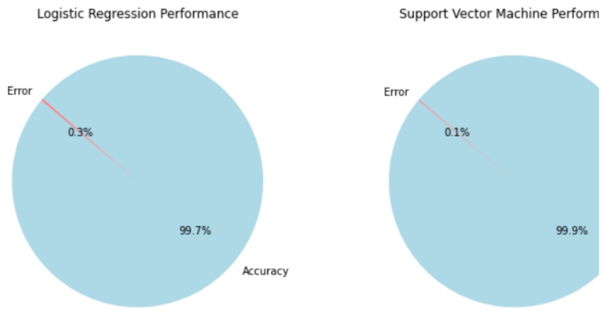
Confusion matrix to find out FP (false positive), FN (false negative), TP (true positive), TP (true negative).

➢ **Bar Graph: -**



The chart above shows the comparison between the LR and SVM test dataset using a bar chart for visualization.

➢ **Pie Chart: -**



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

RESULT AND 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.

POSSIBLE FUTURE EXTENSION

- 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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