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Skeletal Bone Age Classification Using Svm

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Abstract: *Bone Age Assessment (Baa) Is A Method Of Evaluating The Level Of Skeletal Maturation In Children. The Manual Methods Are Prone To The Variability Of Observation, Time-Consuming And Limited To Objective Decisions. Baa Is Purely Based On Measuring The Length And Shape Of Various Bones, So Radiographs Images Are A Must. In This Research Work, A Multi-Scale Structuring Element Is Used To Enhance The X-Ray Of A Left Hand-Wrist Using Circular Shape Structuring Element At Different Scales To Extract Bright And Dark Portions At All Scales And Its Neighboring Scales. The Deep Learning And Neural Network Methods Are Justifiable To Implement When There Is A Large Amount Of Data And Hardware Resources Are Sufficient. But , In Cases When Data Size Is Small And Resources Are Less There Is Need To Find An Accurate Algorithm That Can Work On Small Unimodal Data And Requires Minimum Resources .This Research Work Focuses On Finding An Algorithm That Produces High Accuracy And Low Misclassification Error . The Results Show That Knn And Svm Seem To Fit Into Such Condition As They Have Good Accuracy As Compared To Naïve Bayes .*

***Keywords** -Bone Age Assessment, Hand X-Ray , Feature Extraction ,Svm , Knn, Naïve Bayes .*

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I. INTRODUCTION

Skeletal Maturation Is A Surrogate Of Developmental Age Or Physiological Maturity Which Represents More Truthfully Than Chronological Age Or Determines How Far An Individual Has Progressed Towards Full Maturity And May Hence Be Considered A Sort Of 'Biological Age'. Skeletal Maturation Is Marked By An Orderly And A Reproducible Sequence Of Recognizable Variations In The Appearance Of The Skeleton During Childhood [1].

Bone Age Assessment Is Very Significant In Pediatrics, Especially In The Diagnosis Of Endocrine Logical Problems And Growth Disorders. Based On The Skeletal Improvement Of The Bones In The Left-Hand Wrist [2], Bone Age Is Assessed And Compared With The Chronological Age. A Difference Between These Two Values Indicates Irregularities In Skeletal Development. This Is Used In The Diagnosis Of Endocrine Disorders And Also To Monitor The Therapeutic Effect Of The Treatment. Bone Age Indicates Whether The Growth Of A Patient Is Accelerating Or Decreasing, Based On Which The Patient Can Be Treated With Growth Hormones. Baa Is Widely Used Due To Its Simplicity, Minimum Radiation Exposure, And The Availability Of Multiple Bone Disease Management Centers For Assessment Of Maturity [3].

The Development Of Each Roi Is Divided Into Various Stages, As Shown In Figure 1, And Each Stage Is Given A Letter (A,B,C,D,…I), Reflecting The Development Stage As:

- Stage A – Absent
- Stage B – Single Deposit Of Calcium [4]
- Stage C – Center Is Distinct In The Entrance
- Stage D – Maximum Diameter Is Partial Or More The Width Of Metaphysics
- Stage E – Border Of The Epiphysis Is Dipped
- Stage F – Epiphysis Is As Varied As Metaphysics
- Stage G – Epiphysis Caps The Metaphysis
- Stage H – Fusion Of Epiphysis And Metaphysis Has Begun
- Stage I – Epiphysis Fusion Completed.

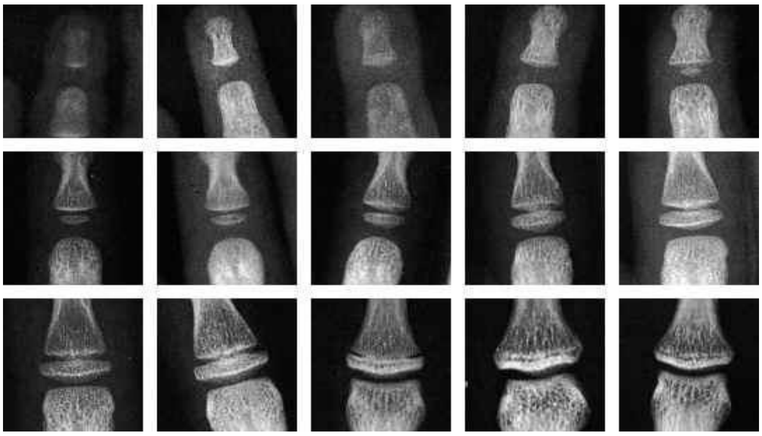

Figure 1. Different Stages Of Bone Development

Baa Is A Radiological Inspection To Determine The Difference Between The Skeletal Bone Age And The Chronological Age (The Real Age Since Birth Date) [5]. This Discrepancy Presents Aberrations In The Skeletal Growing Of Children Or Hormonal Problems. For A Reliable Assessment Of Bone Age (Ba) And Reproducible Method, It Is Not Only A Difficult Process But Also A Time-Consuming Radiological Procedure. Baa Is Based On Three Orders As Follow; (A) Entrance Of Primary And Secondary Middles Of Ossification, (B) Growth Of Both Centers, (C) Timing Of Fusion Of The Primary And Secondary Centers.

1.1 Types Of Bone Age Assessment

1.1.1. Gp Method [6]

The Gp Method Is An Atlas Method In Which Bone Age Is Assessed By Comparing The Radiograph Of The Enduring With The Nearest Standard Radiograph In The Atlas. The Gp Method Was Developed Using Radiographs Of Upper-Middle-Class Caucasian Kids In Cleveland, Ohio, United States, & The Radiographs Were Obtained Between 1931 And 1942. It Has Recently Been Reported That Secondary Sex Characteristics In Current Boys & Girls Begin Earlier Than They Did Numerous Decades Ago In The United States, Therefore, It May Be Difficult To Assess Bone Age Accurately In Current Children Using The Gp Method.

1.1.2. Tw2 Method

There Are Actually 3 Different Tw2 Methods: The Radius-Ulna-Short Bones (Rus) Method For Appraising The 13 Long Or Short Bones (I.E., The Radius, Ulna And Short Bones Of The First, Third & Fifth Fingers), The Carpal Process For Evaluating The 7 Carpals And The 20-Bones Method For Evaluating The 13 Long Or Short Bones And 7 Carpals. For The Purposes Of This Review, The Tw2 Techniques Are Referred To As The Tw2 Technique Hereafter. The Tw2 Method Is A Scoring Method. The Maturity Level Of Each Bone Is Categorized Into A Stage (From Stage A To H Or I). Afterwards, Every Stage Is Replaced By A Score And A Total Score Is Calculated. Finally, The Total Score Is Transformed Into The Bone Age Value [7].

II. RELATED WORK

C. Spampinato Et.Al (2017) [8] Presented Several Deep Learning Methods To Assess Skeletal Bone Age Automatically; The Results Presented An Average Discrepancy Between Manual & Automatic Assessment Of About 0.8 Years, Which Is State-Of-The-Art Performance. Besides, This Is The First Mechanical Skeletal Bone Age Calculation Work Tested On A Public Dataset And For All Age Ranges, Races & Genders, For Which The Source Code Is Obtainable, Thus Representing An Exhaustive Baseline For Future Research In The Field. Besides The Precise Application Scenario, The Writer Aims At Providing Answers To More General Questions About Deep Learning On Medical Images: From The Comparison Between Deep-Learned Features And Manually-Crafted Ones To The Usage Of Deep-Learning Techniques Trained On General Imagery For Medical Difficulties, To How To Train A Cnn With Few Images. Daniela Giordano Et.Al (2016)[9] Presented A Tool For Automatic Assessment Of Skeletal Bone Age According To A Modified Version Of The Tanner And Whitehouse (Tw2) Clinical Method. The Tool Was Able To Provide An Accurate Bone Age Assessment In The Range 0–6 Years By Processing Epiphyseal /Metaphysical Rois With Image-Processing Techniques, And Assigning The Tw2 Stage To Each Roi By Means Of Hidden Markov Models. The System Was Evaluated On A Set Of 360 X-Rays (180 For Males And 180 For Females)Achieving A High Success Rate In Bone Age Evaluation (Mean Error Rate Of 0.41 ± 0.33 Years Comparable To Human Error) As Well As Outperforming Other Effective Methods. P. Thangam Et.Al (2012) [10] Did A Comparative Study On Four Computerized Skeletal Bone Age Assessment (Baa) Methods Using The Partitioning Method. The Four Systems Studied Work

According To The Renowned Tanner & Whitehouse (Tw2) Method, Based On The Region Of Interest (Roi) Taken From The Wrist Bones. The Systems Ensure Accurate & Robust Baa For The Age Range 0-10 Years For Both Girls & Boys. Assumed A Left Hand-Wrist Radiograph As Input, They Estimate The Bone Age By Deploying Remarkable Procedures For Preprocessing, Feature Extraction, And Classification. The Four Baa Systems Differ From Each Other In The Type Of Roi Used, The Feature Extraction Techniques And Finally The Classification. The System's Output The Age Class To Which The Radiograph Is Categorized (Class A – Class J), Which Is Mapped Onto The Final Bone Age. The Systems Were Studied And Their Performances Were Compared By Varying The Partition Of The Train And Test Datasets. The Systems Were Judged Based On The Results Obtained From Two Radiologists. Nikhil Dharman Et.Al (2014) [11] Presented Methods For Assessing Bone Maturity That Include :
1) Greulich And Pyle
2) Tanner And Whitehouse And
3) Eklof And Ringertz.

The Aim Of This Paper Is To Evaluate Or Compare The Results Obtained From Every Bone Age Estimation Methods & Suggests The Best Method Based On The Accuracy And Efficiency [12].

Table 1. Computation Between Related Papers In Bone Age Assessment

Author Name	**Title Name**	**Technique Used**	**Parameters Or Results**
C. Spampinato [2017]	Deep Learning For Automated Skeletal Bone Age Assessment In X-Ray Images.	Deep Learning , Roi	Average In Reading Phase (1,2)
Kashif, Muhammad, And Deserno [2016]	Feature Description With Sift, Surf, Brief, Brisk, Or Freak? A General Question Answered For Bone Age Assessment	Svm Classification Using Sift , Surf , Brief , Brisk Or Freak	Accuracy With 98.36%
D. Giordano [2015]	Modeling Skeletal Bone Development With Hidden Markov Models	Machine Learning , Hidden Markov Models	Tw2 Final Score
P. Thangam [2012]	Comparative Study Of Skeletal Bone Age Assessment Approaches Using Partitioning Technique	Feature Extraction And Classification	Accuracy, Recall, Precision
N. D. M. K And J. C. Moses[2014]	Survey On Different Bone Age Estimation Methods	Er Method, Gp And Tw Method	Accuracy

III. Issues In Bone Age Assessment

The Manual Methods [13]. Of Bone Age Assessment Are Prone To The Variability Of Observations, Is Time-Consuming Hence, This Study Aims To Develop An Automated Method For Baa Based On Machine Learning That Consumes Minimum Overhead .The Work Stimulates The Growing Awareness Of The Need For Bone Age Assessment (Baa) Structures Featuring An Appropriate Methodology For Skeletal Age Estimation. In Most Cases, The Bone Age Is Assessed From The Hand Wrist Radiograph And Then Compared With The Chronological Age. Although Many Research Initiatives Have Been Carried Out, The Problem Of Estimating Accurately The Bone Age Of An Individual Is Far From Being Solved [14]. From The Contemporary Literature Data, It Has Been Found That Use Of Machine Learning In Building Automated Baa Is Limited Although Some Researchers Have Used Deep Learning Also. But, The Biggest Issues In Using Deep Learning Are That It Requires High-Grade Hardware And Huge Dataset. At The Same Time, The Researchers Have Used Neural Networks For Building Baa And It Can Be Seen That This Method Seems To Perform [15](Well In Most Cases. But, In Certain Cases, The Additionally Hidden Layer Architecture Adds More Bytes Of Overhead In Running The Automated System. Hence, To Avoid The Additional Overhead Due To The Hidden Layer Of Network Methods Such As Support Vector Machines Many Are Useful. They Are Especially Useful In Cases, Where Associated Learning Is Learning Between The Variables And Data Can Be Subjected To Regression Analysis For Classification.

IV. Problem Statement

Empirical Experiments On Neural Network And Deep Learning Algorithms Show That There Is Always A Need For Large Dataset And Infrastructure To Run These Algorithms , Hence There Is A Need For Us To Find The Tradeoff Between The Sizes Of The Dataset , Resources Required To Run The Setup . Support Vector Machines Can Help In Such Cases. But Studies In Previously Used Naïve Bayes , K-Nearest Neighbors , And Support Vector Machine Models Also Issues, Especially In Case Of Assigning Or Computing The Weighs/Distance Of Each Class And There Is Always A Need To Find Which Classification Algorithm Would Provide The Best Accuracy.

V. Scope Of Work

This Work Will Be Limited To Working On Age Classification Between The Two Classes Based The Unimodel Data Generated Using Procrustes Alignment Of The Hands Of Subjects Having A Good Age Difference. The Classification Method Will Be Able To Provide Good Quality Of Results In Terms Of True Positive Rate And Misclassification Error. Hence, This Study Will Be Explorative In Nature To Find Which Kernel Produces The Best Accuracy To Find Correct Age.

VI. Implementation

In This Section, The Procedure As Depicted In [2] Figure 2 Has Been Explained To Achieve The Aforementioned Scope Of Work. Care Has Been Taken To Use Well Formulated And Established Practices To Pre-Process The Data And To Evaluate The Kernel Of The Support Vector Machine.

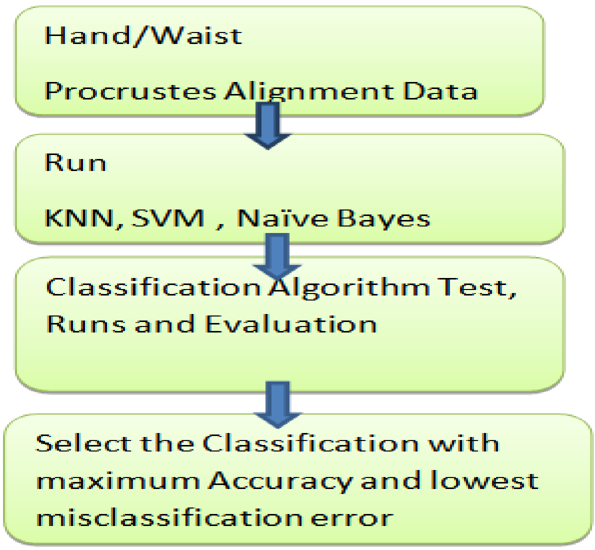

Figure [2] Flow Of The Research Work

Step 1: The First Step Is To Conduct A Procrustes Shape Analysis To Develop A Mathematical Model Of Shape With Respect To The Age Of The Person . This Is Done Using Following Procedures [3].

a) Landmark Analysis: This Is Done To Build A Rough Boundary Of The Hand/Waist From The X-Ray . The Data Consist Of The (X,Y) Coordinates On The Vector Space Model Considered For The Said X-Ray .

x	y
0.000605589100000000	0.0793110132000000
0.00146418880000000	0.0695767552000000
0.00250337690000000	0.0595841706000000
0.00317788520000000	0.0499657877000000
0.00345848800000000	0.0435116738000000
0.00357112920000000	0.0370715782000000
0.00364932370000000	0.0311044473000000
0.00371607650000000	0.0240985714000000
0.00944433550000000	0.0233028773000000
0.0133071868000000	0.0245106220000000
0.0143371867000000	0.0278392658000000
0.0153671876000000	0.0311679076000000
0.0178572927000000	0.0375043079000000
0.0231669378000000	0.0502775237000000
0.0272662230000000	0.0635327473000000
0.0306553338000000	0.0770314261000000
0.0341900475000000	0.0904904082000000
0.0354158655000000	0.0941644013000000
0.0364025384000000	0.0968418717000000

Table 2: Partial List Of Landmarks Of Hand Of 18 Year Boy

These Points Are Selected On A Continuous Surface Of The X-Ray Of The Hand Of The 18-Year-Old Boy. The Next Step Is To Extract And Compute Mean Shape, Standard Deviation, Distance Different Ion Between The Various Landmarks Of All The Images Of Each Class Of Age. The Further Process Can Be Summarized In Following Three Steps:

1) Translation Of Landmarks: The Mean Of The Landmarks Lie Within The Origin As Per The Vector Space Model Of The Hand Object . Mathematically The Sum Of The Entire X' Coordinated Is Divided By Its Frequency And Sum 'Y' Is Divided By Its Same Frequency To Get The Mean . The Mean Values Are Translated So That This Mean Is Translated Into Origin. E.G.
2) Uniform Scaling : In This Step , Instead Of Averages Of X, Y The Components Are Eliminated Using Root Mean Square Distance (Rmsd) From The Points To The Translated Origin .

$$s = \sqrt{\frac{(x_1 - \bar{x})^2 + (y_1 - \bar{y})^2 + \cdots}{k}}$$

The Scale Becomes 1 When The Landmarks Points Are Divided By The Initial Shape Data Point Of X-Rays

$$((x_1 - \bar{x})/s, (y_1 - \bar{y})/s).$$

3) Rotation: In This Step The Rotation Of The Landmarks Is Done On The Basis Of 30 Degrees Of Angle To Eliminate Unwanted Landmarks Point That Does Not Align With Origin.
4) Shape Difference Analysis: This Is Done By Superimposing The Origin And Translated Landmark Points And Square Root Difference Is Taken As Metric To Find The Shape Difference . The Differences Between The Landmarks Between All The Set Of Landmarks As Per Age Class Are Computed And Generalized Shape Is Formed .

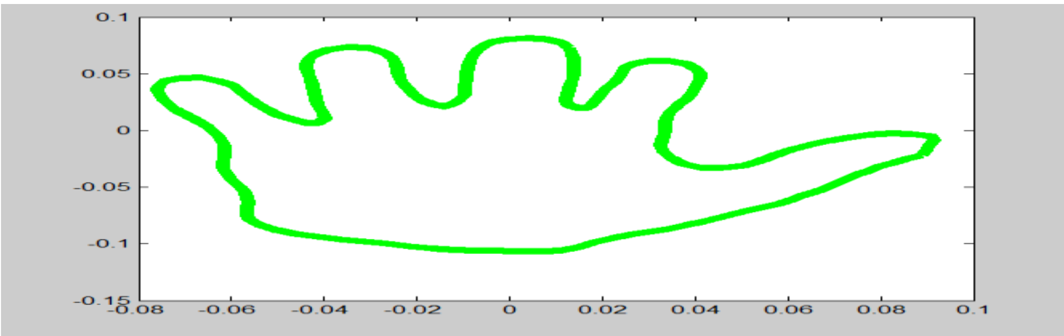

Figure 3: Generalized Mean Shape Of The 18 Year Boy

VII. Classification And Prediction

In This Step, Each Mean Shape Image Is Processed For Extracting Its (X,Y) Data Points (Feature) With Respect To Its Class. We Have Taken 2 Classes: Which Include 12...18 Years Old Boys And These Classes Were Coded As A And B Respectively. As Mentioned In The Scope Of Work, The Intention Is To Find Accuracy Classifier That Works With Small Data Sets Of These Landmarks. The Process Followed Can Be Understood Using [2] Diagram.

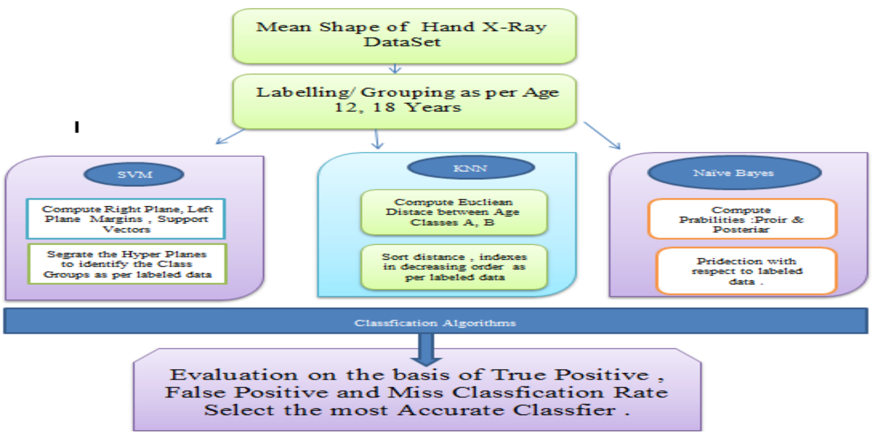

Figure [4] : Classification Flow

The Working Of The Classifiers Is Highlighted In The Figure [4] . And The Main Advantage Of This Entire Algorithm Is That They Are Easy To Implement And Produce Small Overhead To Handle Small Dataset. The Svm Classifier Primarily Works On The Principle Of Find Hyper-Planes And Margins Between The Two Classes (12-Year And 18-Year Old Hand) .It Learns This Pattern From The Labeled Data Given To It. The K-Nearest Neighbor Algorithm Works On The Principle Of Distances Between The Similar Classes Of Objects. The Naïve Bayes Classifier Finds The A Priori And A Posteriori Probabilities With Respect To The Supervised Data Given To It For Training And Learning. The Next Section Discusses The Outcomes Of These Algorithms To Achieve The Objectives Of This Research Work.

VIII. Results

The Evaluation Of All These Algorithms Has Been Done On The Basis Of Ten Evaluation Parameters That Are Highly Effective In Evaluating All The Aspects Of The Supervised Learning Classification Algorithms That Work On Small Datasets.

1) Knn Algorithms Evaluation: It Can Be Seen From The Figure [5] That The Accuracy Of The Knn Is Quite High As It Has A High Percentage (96.4) Of True Positive And Low Number False Alarm. A Similar Trend Is Reflected In The Values Of Sensitivity (0.96) And Specificity (0.98) .

```
For kNN algorithm:
 True Positive, TP - 140,
 True Negative, TN - 48,
 False Negative, FN - 3,
 False Positive, FP - 4
 Total Rows-      195
 Positive Predicted Value, PPV = 0.97
 Negative Predicted Value, NPV = 0.94
 Specificity, SP = 0.92
 Sensitivity, SE = 0.98
 Accuracy = 96.41%
 Geometric Mean = 1.38.
```

Figure [5] Knn Evaluation Outcome

This May Be Attributed To The Fact That There Is A Good Amount Of Elucidation Distance Between The Landmarks Point Of A 12-Year Boy And 18-Year Boy Hand . The Knn Algorithm Clearly Is Able To Pick This From The Dataset As It Is Able To Learn This From The Labeled Data. The Central Tendency Or Mean In Terms Of Geometric Mean (1.38) Show That There Is Some Degree Of Imbalances In The Data But It Is Low .

2) Support Vector Machine Algorithmevaluation: The Performance Of The Svm Is Also Good In Terms Of Its Accuracy As Compared To The Knn Algorithm. This May Be Attributed To The Fact That There Is The Clear-Cut Demarcation Of The Term Lines (Hyper-Planes) In The Dataset. The Accuracy (96.41) Is Similar To Knn But The Number Of True Positives Is Less As Compared To Knn. A Similar Trend Can Be Inferred From The Values Sensitivity And Specificity. And The Proposition Ratio Of The Positive Predicted To Negative Predicted Values Is Almost Close To 0.99, Which Is A Good Sign.

```
Support Vector Machine Linear kernel function
 True Positive, TP - 138,
 True Negative, TN - 50,
 False Negative, FN - 2,
 False Positive, FP - 5
 Total Rows -      195
 Positive Predicted Value, PPV = 0.97
 Negative Predicted Value, NPV = 0.96
 Specificity, SP = 0.91
 Sensitivity, SE = 0.99
 Accuracy = 96.41%
 Geometric Mean = 1.38.
```

Figure [6] Svm Evaluation Outcome

3) Naïve Bayesian Classification Algorithm Evaluation: This Algorithm's Performance Is The Lowest Among All The Algorithms Evaluated. Its Accuracy Is 26.7% And Has The Lowest Number Of True Positives.

Further Analysis Shows That A Classifier That Works On The Principle Of Distances Work Better And The One That Works On The Probabilities In The Context Of Bone Age Classification .

```
For Bayesian Classification:
 True Positive, TP - 0,
 True Negative, TN - 52,
 False Negative, FN - 143,
 False Positive, FP - 0
 Total  Rows -      195
 Positive Predicted Value, PPV = NaN
 Negative Predicted Value, NPV = 0.27
 Specificity, SP = 1.00
 Sensitivity, SE = 0.00
 Accuracy = 26.67%
 Geometric Mean = 1.00.
```

Figure 7. Naïve Bayesian Classification Algorithm Evaluation

IX. Conclusion And Future Scope

It Is Apparent From All The Above Outcomes That Svm And Knn Have Similar Percentages In Terms Of The Proportion Of True Positives And False Positives. The Accuracy Both These Algorithms Is Similar 96.41%. From The Results, We Can Conclude That Distance Classifiers Are Best Suited For Building Automated Bone Age Classifiers. The Evaluation Process Was Able To Cover All Aspects Of Checking The Performance Of The Algorithms, Hence It Can Also Be Inferred That Misclassification Rate Will Be Low In Cases Of Svm And Knn Algorithms

For Future Scope, This Work Can Be Extended By Adding Two More Classes I.E. Male And Female. Separate Feature Vectors Can Be Male And Female Classes With Their Age Brackets. Another , Way To Extend This Work Use Features From The Feet And Toe To Come Up With New Shape Model And Run Supervised Learning Algorithms To Automate It .

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