Application of structural and textural features from X-ray images to predict the type of bone fracture treatment

ANAM HAQ, SZYMON WILK

ERASMUS MUNDUS JOINT DOCTORATE PROGRAM(IT4BI-DC)

POZNAN UNIVERSITY OF TECHNOLOGY

Agenda

- Introduction
  - Problem Investigation and Proposed Solution
- Literature Review
- Feature Description
  - Extraction of Structural Features
  - Extraction of Textural Features
- Data Description and Experimental Evaluation
- Results
- Conclusion
- Future Work

Introduction

- Manual Examination are *time consuming* and *tedious*
- Prone to error which results in *misdiagnosis*, i.e., *inadequate treatments*
- Surgical treatments are *expensive* and painful
- *Clinical (imaging) decision models* largely rely on *segmentation* and *feature extraction*
- Domain knowledge is necessary when creating *automated* approach for *detecting abnormalities* from the images
- Abnormalities in the images can be *identified* either by their *structure (shape)* or by their texture (content)

Problem Investigation & Proposed Solution

Underlying Problem

Previous decision support systems were build to identify bone fractures based on either structural feature or textural features

Proposed Solution

Our goal was to evaluate the usefulness of structural and textural features, and benefits resulting from their integration

Literature Review

Preprocessing

Segmentation

Feature Extraction

No.	Author	Part	Used Approaches
1	Vijay Kumar et al.	Preprocessing	Noise removal using Gaussian filter
2	Chai et al.	Preprocessing	Noise removal using Laplacian filter
3	Aishweariya et al.	Segmentation	Edge detection and active contour modeling
4	Smith et al.	Segmentation	Discrete wavelet transformation
5	Aishweariya et al.	Fracture Detection	Gray level Co-occurence matrix(GLCM)
6	Myint et al.	Fracture Detection	Hough Transformation

Features Description

Feature Names	Category	Description
Mean Hough Peak	*Structural Features*	*Mean of peak values* selected from Hough transformation.
Standard Deviation Hough Peak		*Standard deviation of peak values* selected from Hough transformation.
Contrast	*Textural Features (GLCM)*	Measure of the *intensity contrast* between a pixel and its neighbour over the whole image
Energy		Measure of *uniformity* in an image over a selected region
Homogeneity		Measure the *degree of closeness* between values in the grey-level co-occurrence matrix
Correlation		Measure of how *correlated* a pixel is to its neighbour over the whole image

*Hough transformation is an algorithm used to detect certain shapes from an image

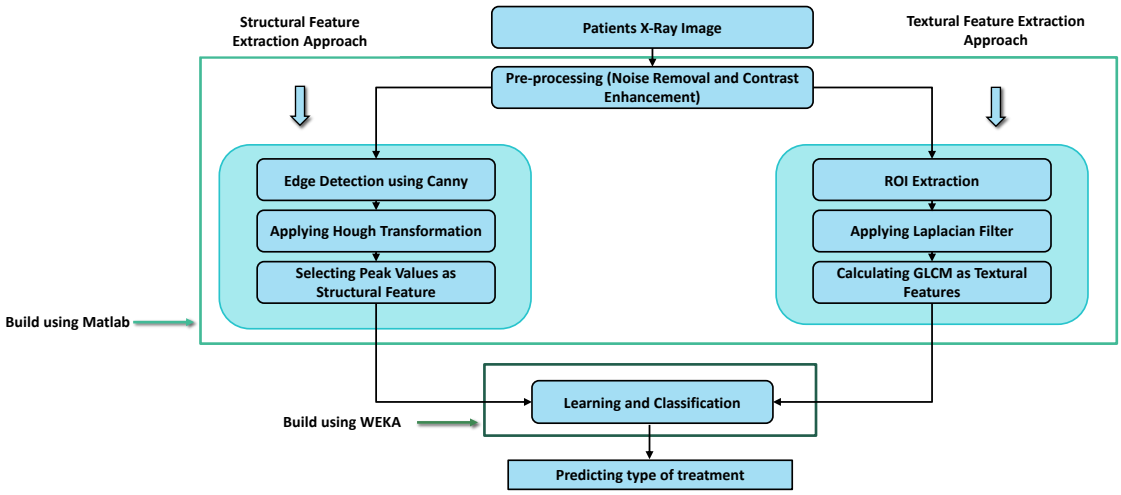


Figure 1:Proposed System Architecture

Extraction of Structural Features

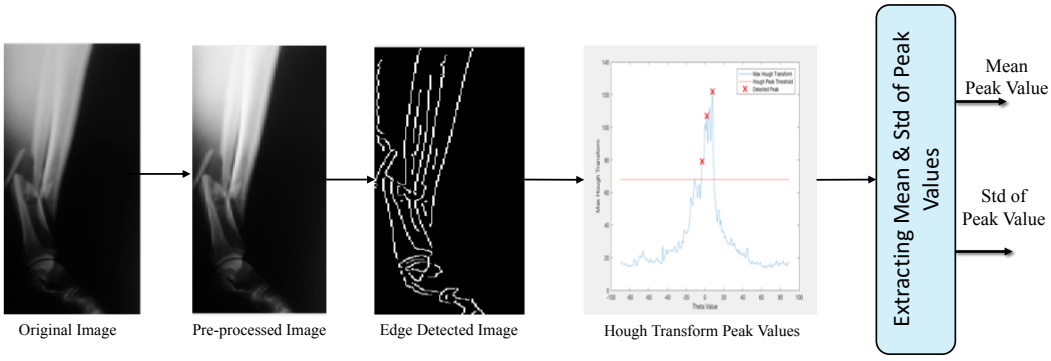


Figure 2: Structural Feature Extraction

Extraction of GLCM Features

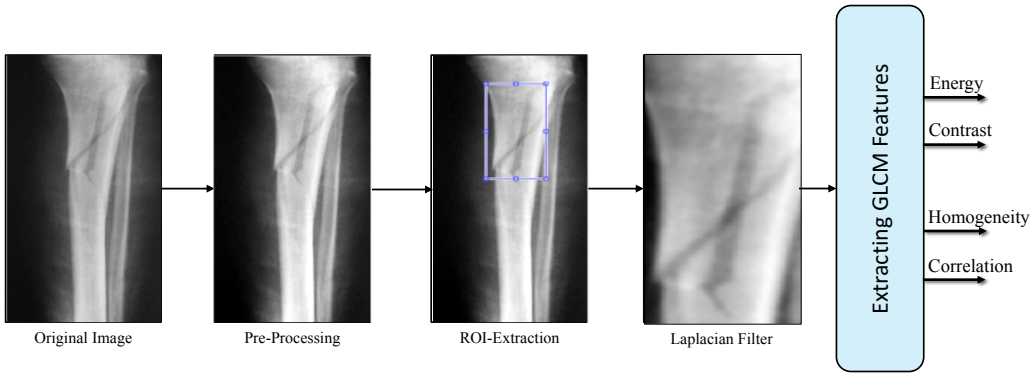
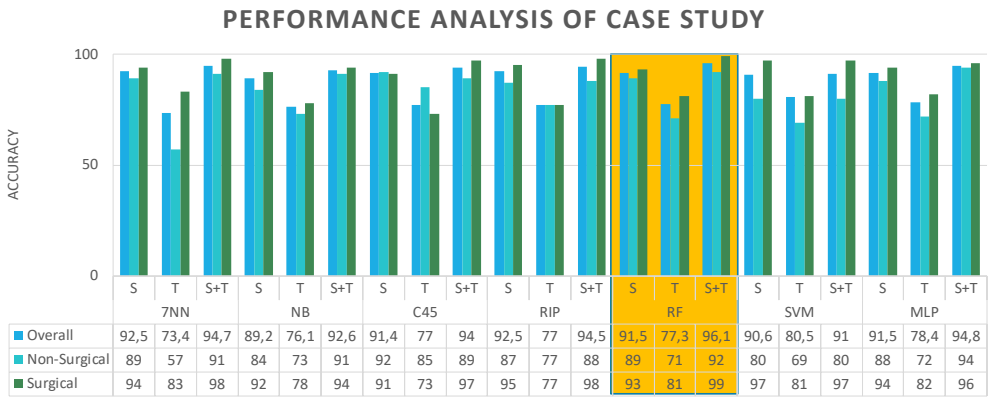


Figure 3: Textural Feature Extraction

Data Description and Experimental Evaluation

1. Dataset under consideration was obtained from X-ray images coming from the data repository provided by the *Wielkopolska Centre of Telemedicine*
2. Total of *2030 patients* with *bone fractures* –
   a. *1593 (78.5%)* underwent a *surgery and,*
   b. *437 (21.5%)* were treated *non-surgically*
3. *Randomly* selected 210 patients –
   1. 134(63.8%) *surgical* cases and,
   2. 76 (36.2%) *non-surgical*
4. Considered classifiers that yield the best results are
   1. K-nearest neighbour classifier with *k=7 (7NN),*
   2. Naive Bayes classifier *(NB)*,
   3. Tree-based classifier induced with the C4.5 algorithm *(C45)*,
   4. Rule-based classifier induced using the RIPPER algorithm *(RIP)*,
   5. Random forest classifier *(RF)*,
   6. Support vector machine classifier *(SVM) (gamma = 0.01, cost = 10^6)* and,
   7. Multilayer perceptron classifier *(MLP) (3-hidden layers)*
5. The *evaluation measure* considered for experimental analysis is *overall accuracy* reported by the mentioned classifiers
6. Accuracy of *overall system* is reported along with the accuracy of *individual classes* (surgical, non-surgical)

Results



	S	T	S+T	S	T	S+T	S	T	S+T	S	T	S+T	S	T	S+T	S	T	S+T	S	T	S+T
	7NN			NB			C45			RIP			RF			SVM			MLP		
Overall	92,5	73,4	94,7	89,2	76,1	92,6	91,4	77	94	92,5	77	94,5	91,5	77,3	96,1	90,6	80,5	91	91,5	78,4	94,8
Non-Surgical	89	57	91	84	73	91	92	85	89	87	77	88	89	71	92	80	69	80	88	72	94
Surgical	94	83	98	92	78	94	91	73	97	95	77	98	93	81	99	97	81	97	94	82	96

Conclusion

1. *Structural features -- a better predictor for the type of treatment a patient should undergo*
2. *Improvements were observed when structural features were integrated with textural features*
3. *Extraction of different type of features is not an easy and requires manual segmentation*

Future Work

1. *Incorporate more data*
2. *Automate the process of segmentation*
3. *Performance of the current model with convolutional neural network (CNN)*
4. *Educational tool development at Wielkopolska Centre of Telemedicine platform aiming to help physicians and students to practice their decision making skills*