

Machine Learning Techniques For Medical Diagnosis Of Diabetes Using Iris Images

MMI 700: Research Methods

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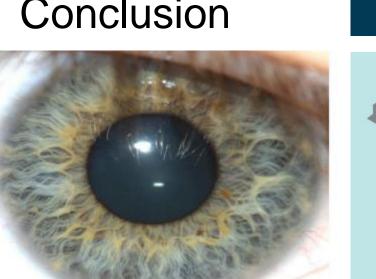
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Introduction



- Introduction
- Abstract
- Discussion
- Results
- Conclusion





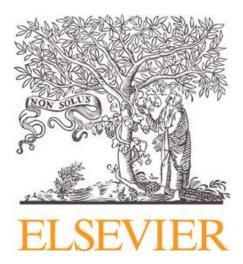


Introduction



Machine learning techniques for medical diagnosis of diabetes using iris images

Iris Diabetes Classification Segmentation Feature extraction Disease diagnosis



Thapar University, Patiala, India Accepted 10 January 2018

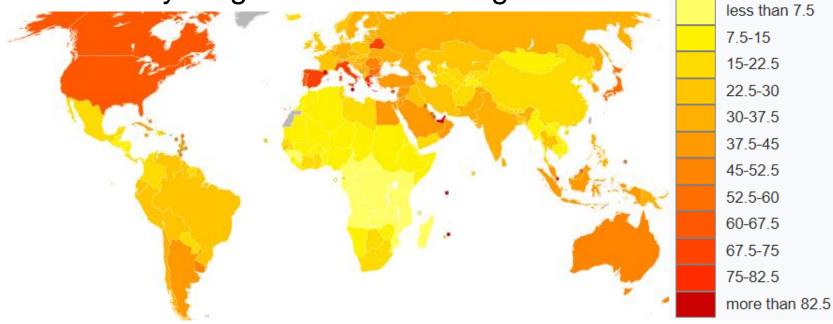
Piyush Samant, Ravinder Agarwal

- **Circular Hough transform** used for segmentation,
- **Daugman's rubber sheet model** used for normalization,
- Gabor filter and 2-D DWT based features

https://www.sciencedirect.com/science/article/ pii/S0169260717304649

Introduction

- Diabetes:
 - 381.8 million people are affected
 - excessive blood sugar level
 - late diagnosis leads to advert effects
 - early diagnosis is a challenge



Prevalence of diabetes worldwide (per 1000 inhabitants).

Abstract



- Diabetes is about pancreatic enzyme Insulin
- Complementary-Alternative Medicine (CAM)
- Digital image processing
- Best classification accuracy 89.63% RF classifier
- Effective and diagnostically significant model for noninvasive and automatic diabetes diagnosis.

Classification

Identifying to which category an object belongs to.

 Applications: Spam detection, Image recognition.

 Algorithms: SVM, nearest neighbors, random forest, ...

 — Examples

Regression

Predicting a continuous-valued attribute associated with an object.

Applications: Drug response, Stock prices. **Algorithms**: SVR, ridge regression, Lasso,

Examples

Clustering

Automatic grouping of similar objects into sets.

Applications: Customer segmentation, Grouping experiment outcomes Algorithms: k-Means, spectral clustering, mean-shift, ... — Examples

Dimensionality reduction

Reducing the number of random variables to consider.

Applications: Visualization, Increased efficiency

Algorithms: PCA, feature selection, non-

Model selection

Comparing, validating and choosing parameters and models.

Goal: Improved accuracy via parameter tuning **Modules**: grid search, cross validation,

Preprocessing

Feature extraction and normalization.

Application: Transforming input data such as text for use with machine learning algorithms. **Modules**: preprocessing, feature extraction.

Discussion

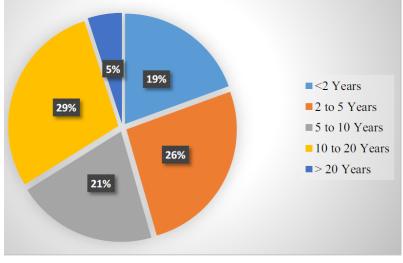


Subject Selection and Data Collection



- Non-contact IR imaging
- Varied diabetic states of 1-25 years

Distribution of subjects according to duration of diabetic stste

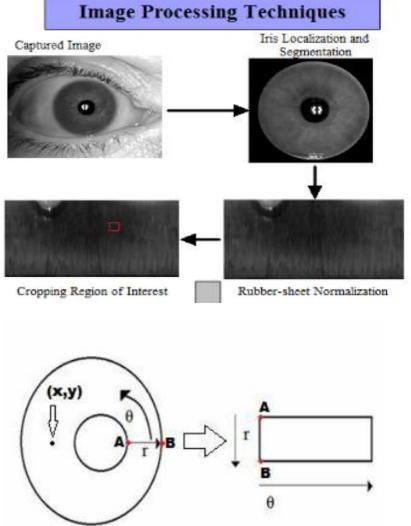


| | No. of male | No. of female | Gender ratio | Average age | Standard deviation | Total |
|----------------------|----------------|------------------|-----------------|----------------|-----------------------|-------|
| Diabetic subjects | 102 | 78 | 1.307 | 53.32 | 8.56 | 180 |
| Healthy subjects | 91 | 67 | 1.35 | 52.86 | 9.98 | 158 |

Discussion



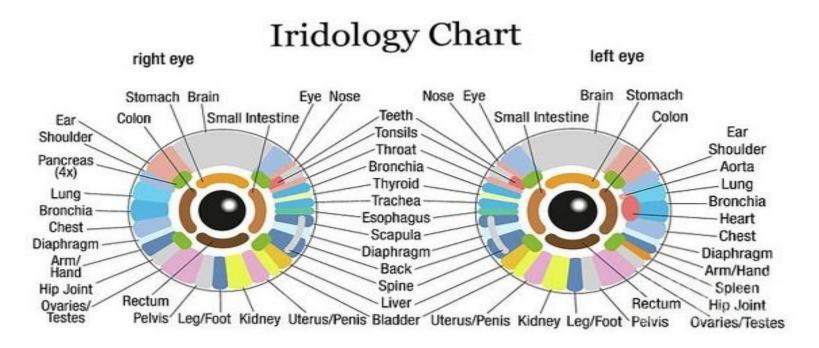
- Input: Gray IR images
 640 ×480 (VGA) of each
 iris
- Iris segmentation (Circular Hough transform)
- Rubber-sheet normalization
- Output: Homogeneous 2D array of 360 ×720



Discussion



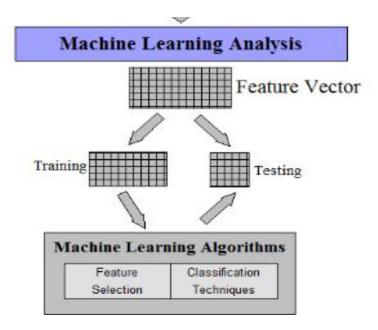
- The Region of Interest (ROI) cropped from the rubber sheet normalized iris.
- Green areas in the chart indicate pancreas (source of Insulin enzyme which balances blood sugar)



| Mert Çağlar | Discuss | |
|-----------------------------------|--|--|
| Textural features | Formulas | Feature Extraction |
| Contrast | $\sum_{i,j} i-j ^2 P(i,j)$ | Statistical Features |
| Correlation | $\sum_{i,j}(i-\mu_i)(j-\mu_j)P(i,j$ | Texture Based Features Wavelet Based Features |
| Energy | $\sum_{i,j} P(i, j)^2$ | Discrete Wavelet Transforms (DWT |
| Homogeneity | $\sum_{i,j} \frac{\mathbf{P}(i,j)}{1+ i-j }$ | |
| Statistical features | | Formulas |
| Mean intensity | | $\frac{1}{N}\sum_{i=1}^{N}X(i)$ |
| Standard deviation | | $\left(\frac{1}{(N-1)}\sum_{i=1}^{N}(X(i)-\bar{X})^2\right)^{1/2}$ |
| Entropy Histogram intensity fe | eatures | $\sum_{i=1}^{N_1} P(i) . \log_2 P(i)$ Five histogram intensity levels |

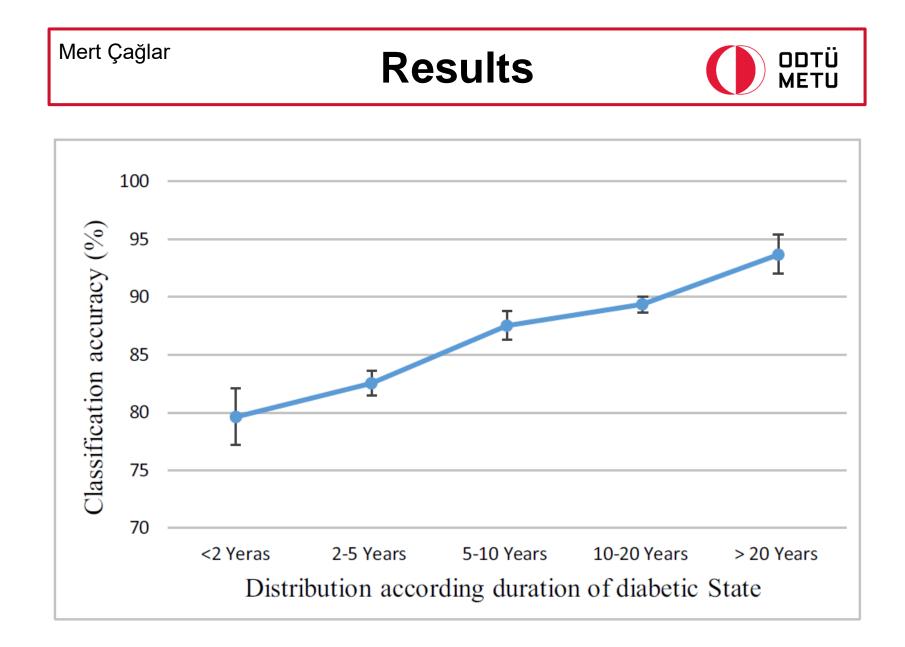
Results





- Binary Tree Model (BT),
- Support Vector Machine (SVM)
- Adaptive Boosting Model (AB)
- Generalized Linear Models (GL)
- Neural Network Model (NN)
- Random Forest (RF)
 Classifiers have been trained using the repeated 10 fold cross
 validation technique.

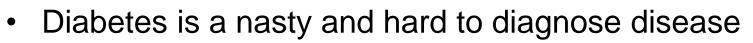
| Feature selection method | Formula for relevance index or scoring criteria Specification | | |
|--------------------------|--|--|--|
| Fisher score | $J_{fisher}(X_{k}) = \frac{\sum_{m=1}^{2} n_{m} (\mu_{k,m} - \mu_{k})^{2}}{\sum_{m=1}^{2} n_{m} \sigma_{k,m}^{2}}$ | X_k =feature to be evaluated, μ_k =overall mean of feature to be evaluated, m=no of samples in mth class, $\mu_{k,m}$ =mean of (X_k) on mth class and $\sigma_{k,m}^2$ =variance of (X_k) on mth class. | |
| <i>t</i> -test | $J_{ttest}(X_k) = \frac{\mu_1 - \mu_2}{\sqrt{\frac{\sigma_1^2}{n_1} - \frac{\sigma_2^2}{n_2}}}$ | μ_1 and μ_2 =means of two classes σ_1 and σ_2 =variance of two classes | |
| Chi-square test | $J_{chi-square}(X_k) = \sum_{i=1}^r \sum_{m=1}^2 \frac{(n_{im}-\mu_{im})^2}{\mu_{im}}$ where, $\mu_{im} = \frac{n_{*m}n_{i*}}{N}$ | n_{im} =no of samples with ith feature value in mth class, n_{i^*} =no of samples with ith feature value n_{*m} = no of samples in class m and N no of samples | |



Questions & Conclusion

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- Digital image processing and machine learning algorithms can create complementary-alternative medical possibilities
- Introduce similar methods to commonly available smartphones/selfie industry
- Identify other diseases from iridology chart and DSP ML methods
- Improve the results with worldwide data collection
- What do you think about the topic?

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