

**COMPUTER-AIDED EXTRA-PULMONARY
TUBERCULOSIS DIAGNOSIS USING IMAGE
PROCESSING AND HMLP NETWORK**

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UNIVERSITI MALAYSIA PERLIS

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**COMPUTER-AIDED EXTRA-PULMONARY
TUBERCULOSIS DIAGNOSIS USING IMAGE
PROCESSING AND HMLP NETWORK**

by

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DECLARATION OF THESIS

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LIST OF ABBREVIATIONS

AFB	Acid-fast bacilli
AI	Artificial intelligence
AIDS	Acquired immune deficiency syndrome
ANN	Artificial neural network
ASRG	Automatic seeded region growing
BCG	Bacille Calmette-Guerin
BP	Backpropagation
CL	Confidence level
CT	Computed tomography
CXR	Chest x-ray
DA	Discriminant analysis
DNA	Deoxyribonucleic acid
ELM	Extreme learning machine
EPTB	Extra-pulmonary tuberculosis
FN	False negative
FP	False positive
GB	Gigabyte
GUI	Graphical user interface
HIV	Human immunodeficiency virus
HMLP	Hybrid multilayered perceptron
H ² MLP	Hierarchical hybrid multilayered perceptron
HSI	Hue, saturation, intensity
HUSM	Hospital Universiti Sains Malaysia
IGRA	Interferon Gamma Release Assays

IP	Image processing
kNN	<i>k</i> -Nearest neighbour
LDA	Linear discriminant analysis
LM	Levenberg-Marquardt
LED	Light-emitting-diode
LED-FM	Light-emitting-diode fluorescence microscope
LJ	Lowenstein-Jensen
MELM	Modified Extreme Learning Machine
MDR-TB	Multidrug-resistant tuberculosis
MI	Mutual information
MLP	Multi layer perceptron
MRI	Magnetic resonance imaging
mRMR	Minimal-Redundancy-Maximal-Relevance
MRPE	Modified recursive prediction error
MRPE-MELM	Modified Recursive Prediction Error – Modified Extreme Learning Machine Algorithm
MTB	<i>Mycobacterium tuberculosis</i>
NAAT	Nucleic acid amplification test
NN	Neural network
p-HMLP	Parallel hybrid multilayered perceptron network
PNN	Probabilistic neural network
PPD	Purified protein derivative
PTB	Pulmonary tuberculosis
QDA	Quadratic discriminant analysis
RAM	Random-access memory
RBC	Red blood cell
RBF	Radial basis function

RGB	Red, green, blue
RNA	Ribosomal ribonucleic acid
RLS	Recursive least square
RPE	Recursive prediction error
SLFN	Single-hidden layer feedforward network
SSE	Sum of square error
SVM	Support Vector Machine
TB	Tuberculosis
TN	True negative
TP	True positive
TST	Tuberculin skin test
WHO	World Health Organization
XDR-TB	Extensively drug-resistant tuberculosis
ZN	Ziehl-Neelsen

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LIST OF SYMBOLS

$I_1 - I_6$	Affine moment invariants
$\sigma_{between}^2$	Between-class variance
b	Bias
μ_{pq}	Central moment of order $(p + q)$ of an object
c_l	Centre with the largest fitness
c_s	Centre with the smallest fitness
c_j	Cluster centre
$J(\hat{\Theta})$	Cost function
β_{lm}	Decay rate
d_{svm}	Degree of polynomial kernel
$y_k(t)$	Desired (target) output
D_1	Dispersion
D_2	Dispersion
ε	Eccentricity
E	Ellipticity
\mathbf{e}	Error vector
$\hat{\Theta}$	Estimated parameter vector
d_{ji}	Euclidean distance between x_i and c_j .
$f(c_j)$	Fitness of j -th centre
$\lambda(t)$	Forgetting factor

$\psi(t)$	Gradient of the one-step-ahead predicted output
H	Hidden layer output matrix
$\phi_1 - \phi_7$	Hu's moment invariants
H_{hsi}	Hue of HSI colour model
θ_{c-y}	Hue of C-Y colour model
I	Identity matrix
$f(x, y)$	Image pixel value
$f_{gf}(x, y)$	Image pixel value after applying global fixed thresholding
$f_l(x, y)$	Image pixel value after applying local adaptive thresholding
$f_b(x, y)$	Image pixel value in binary
x	Input signal
I_{hsi}	Intensity of HSI color model
J	Jacobian matrix
$p(x, y)$	Joint probabilistic density for feature x and y
γ_{svm}	Kernel parameter
$\alpha_g(t)$	MRPE learning rate
μ_{lm}	Levenberg-Marquardt learning rate
$T_{n,local}$	Local threshold value
Y_{c-y}	Luminance of C-Y colour model
$p(x)$	Marginal probabilistic density function for feature x
$p(y)$	Marginal probabilistic density function for feature y
A_{max}	Maximum of predefined size

r_{\max}	Maximum radius
γ	Maximum range of an activation function
μ	Mean
μ_{bck}	Mean intensity of the background
μ_{obj}	Mean intensity of the objects
$\bar{x}_{n,local}$	Mean of local intensity distribution of n -th region
μ_{ji}	Membership function
A_{\min}	Minimum of predefined size
r_{\min}	Minimum radius
m_{pq}	Moment of order $(p + q)$ of an object
$\alpha_m(t)$	Momentum
\mathbf{H}^\dagger	Moore-Penrose generalized inverse
$I_{mi}(x, y)$	Mutual information for feature x and y
\hat{y}	Neural network output
η_{pq}	Normalized central moment of order $(p + q)$ of an object
N_{c_j}	Number of pixels belong to centre c_j
BG^+	Number of correctly segmented background pixel
TB^+	Number of correctly segmented TB pixel
N_h	Number of hidden nodes
BG^-	Number of incorrectly segmented background pixel
TB^-	Number of incorrectly segmented TB pixel
N_i	Number of input nodes