DECLARATION BY THE CANDIDATE

I do hereby declare that the thesis titled "**Development of Fast Learning-based Approaches for Super-resolution of Multispectral Remote Sensing Images**", submitted to the Department of Electronics and Communication Engineering, Tezpur University, Tezpur, Assam, is a record of original research work carried out by me. All sources of assistance for my PhD work have been duely acknowledged. I also declare that neither this work as a whole nor a part of it has been submitted to any other University or Institute for the award of any degree or diploma.

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CERTIFICATE OF THE SUPERVISOR

This is to certify that the thesis titled "**Development of Fast Learning-based Approaches for Super-resolution of Multispectral Remote Sensing Images**", submitted to the School of Engineering, Tezpur University in part fulfillment for the award of the degree of Doctor of Philosophy in Electronics and Communication Engineering is a record of research work carried out by **Ms. Trishna Barman** under my supervision and guidance.

All help received by her from various sources have been duly acknowledged.

No part of this thesis has been submitted elsewhere for the award of any other degree or diploma to the best of my knowledge.

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Acknowledgements

I would like to express my heartfelt gratitude to all the individuals who have supported me throughout my journey of completing this PhD thesis. First and foremost, my deepest gratitude goes to my supervisor Prof. Bhabesh Deka, for his unwavering guidance, encouragement, and support throughout my research. His expertise and insights have been crucial in structuring my research work. My Ph.D. journey would not have been possible without his belief in my research ability, patience, and scientific and moral support throughout my research. He was available whenever needed and provided me all the research facilities to complete my Ph. D.

I also extend my sincere appreciation to Prof. Bhabesh Deka, the Head, Department of ECE, for his constant support and the excellent resources he has made available to me during my research. I am also grateful to the members of my doctoral committee, Prof. Partha Pratim Sahu and and Prof. Nayan Moni Kakoty, for their constructive feedback, valuable suggestions, and enthusiastic support.

I would also like to express my gratitude to the funding agency ISRO-RESPOND for providing financial support for my research work. Without their support, it would have been impossible for me to carry out this research. I extend my gratitude to National Remote Sensing Centre (NRSC), Hyderabad, and in particular to Mr. A. V. V. Prasad, Deputy Director, NRSC for providing the continuous support and advice during annual progress review meetings held at NRSC.

I would like to acknowledge the support provided by other faculty members, technicians, and my research scholar friends in the department. I owe a special debt of gratitude to my senior lab mate Dr. Helal Uddin Mullah for his constant support, guidance, and encouragement. I am also grateful to my junior lab mates of Intelligent Imaging & Vision Research Lab, Tezpur University for creating a positive research environment to conduct my research work.

I owe a great debt of gratitude to my loved ones, specially my grandmother and my uncle Deba Kumar Bharali, for all of the help and encouragement they have given me over the years. Last but not least, I am indebted to my parents, brother, and my husband for all the sacrifices they have made for me as well as their constant love, support, and encouragement in all of my decisions. In conclusion, I express my heartfelt thanks to everyone who has contributed to my PhD journey, and without whose support, this thesis would not have been possible.

Trishna Barman

Trishna Barman

Dedicated To

My Parents, My Brother & My Respected Teachers
for their great support and encouragement

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Abbreviations

AID	Aerial image database
ADMM	Alternating direction methods of multipliers
BPDN	Basis pursuit denoising
CA	Channel attention
CCD	Charge-couple device
CDLSR	Coupled dictionary learning for super-resolution
CFSRCNN	Coarse-to-fine SR via CNN
CRR	Collaborative sparse representation
CNN	Convolutional neural network
CUDA	Compute unified device architecture
DASR	Degradation-aware SR network
DCT	Discrete cosine transform
DoG	Difference of Gaussian
DL	Deep learning
EN	Entropy
ERGAS	Erreur relative globale adimensionnelle de synthese
FFT	Fast Fourier Transform
FISTA	Fast iterative shrinkage thresholding algorithm
FT	Fourier transform
RG	Residual groups
RS	Remote sensing
GFN	Gated fusion network
GAN	Generative adversarial network
GP-GPU	General purpose graphics processing unit
IBP	Iterative back projection
JSRDNet	Joint dual-branch SR and deblur network
HR	High-resolution
HSENet	Hybrid-scale self-similarity exploitation network
LFF	Local feature fusion

LISS-III	Linear imaging self-scanner-3
LISS-IV	Linear imaging self-scanner-4
LR	Low-resolution
MAP	Maximum a posteriori
MISR	Multiple-image super-resolution
ML	Maximum likelihood
MS	Multispectral
MSSIM	Mean structural similarity
NIQE	Natural image quality evaluator
NIR	Near infrared
NLTV	Non-local total variation
MS	Multispectral
NN	Neural network
OMP	Orthogonal matching pursuit
PSNR	Peak single-to-noise ratio
SAM	Spectral angular mapper
SAN	Second-order attention network
sCC	Spatial correlation coefficient
ScSR	Sparse Coding Super-resolution
SIFT	Shift-invariant feature transform
SISR	Single-image super-resolution
SR	Super-resolution
RS	Remote sensing
ReLU	Rectified linear unit
RSCSE	Residual spatial and channel squeeze-and-excitation
SCSE	Spatial and channel squeeze-and-excitation
SRCNN	SR using convolutional neural network
SRR	Super-resolution reconstrution
SVD	Singular value decomposition
SVM	Support vector machine
TV	Total variation

UIQI	Universal image quality index
VDSR	Very deep CNN-based SR

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Symbols

$\mathbf{A}$	Sparse representation matrix
$\boldsymbol{\alpha}$	Sparse coefficient vector
$\mathbf{D}_c$	Coupled dictionary
$\mathbf{D}_{c\_keypoint}$	Coupled keypoint-driven dictionary
$\mathbf{D}_{c\_patch}$	Coupled patch-based dictionary
$\mathbf{D}_h$	HR dictionary
$\mathbf{D}_{h\_patch}$	Patch-based HR dictionary
$\mathbf{D}_{h\_keypoint}$	Keypoint-driven HR dictionary
$\mathbf{D}_\ell$	LR dictionary
$\mathbf{D}_{\ell\_keypoint}$	Keypoint-driven LR dictionary
$\mathbf{D}_{\ell\_patch}$	Patch-based LR dictionary
$\mathbf{F}_{Deblur}$	Deblur feature maps
$\mathbf{F}_{fusion}$	Fused feature maps
$\mathcal{F}_{LFF}$	LFF module
$\mathbf{F}_{SR}$	SR feature maps
$\mathcal{F}_{SCSE}$	SCSE module
$\mathcal{F}_{UP}$	Upscaling and reconstruction module
G_{scse}	SCSE-based gated module
H	Blurring operator
$\mathcal{L}()$	Loss function
λ	Regularization parameter
$\|.\|_0$	ℓ_0-norm
$\|.\|_1$	ℓ_1-norm
$\|.\|_2$	ℓ_2-norm
$P(.)$	Patch extraction operator
S	Downsampling operator
σ	Standard deviation
θ	Network parameter
$\mathbf{X}$	HR image

$\mathbf{X}_h$	HR training patch matrix
$\mathbf{X}_{keypoint}$	Keypoint-driven HR patch matrix
$\mathbf{X}_{patch}$	HR patch matrix
$\mathbf{Y}$	LR image
$\mathbf{Y}_\ell$	LR training patch matrix
$\mathbf{Y}_{keypoint}$	Keypoint-driven LR patch matrix
$\mathbf{Y}_{patch}$	LR patch matrix
$\mathbf{Z}$	Sparse representation matrix for combined LR-HR patch vectors

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