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Spondylitis Detection Using Deep Learning Architecture

B. AmarnathReddy[1], C.AKSHAYA SABITHA JASMINE [2]
ASSISTANT PROFESSOR[1] MCA SCHOLAR[2]
DEPARTMENT OF MASTER OF COMPUTER APPLICATIONS
QIS COLLEGE OF ENGGINEERING & TECHNOLOGY, ONGOLE
VENGAMUKKAPALEM(V), ONGOLE, PRAKASAM DIST,ANDHRA PRADESH-523272

ABSTRACT

Spondylitis is a chronic inflammatory disease that primarily affects the spine and can lead to severe pain, stiffness, and eventually spinal deformity. Traditional methods for diagnosing spondylitis rely heavily on radiographic interpretation by specialists, which can be time-consuming and subjective. With the growing availability of medical imaging data and advancements in computational capabilities, there is a rising interest in the automation of diagnostic processes through deep learning.

This project presents a deep learning-based solution for the automated detection of spondylitis using spinal X-ray and MRI images. The proposed system employs advanced convolutional neural networks (CNNs) capable of learning hierarchical features from medical images. By training the model on labeled datasets, it can differentiate between healthy and affected spinal structures with high accuracy. The system is designed to reduce diagnostic delays and improve reliability by minimizing human error.

In conclusion, this deep learning architecture provides a promising tool for early and accurate detection of spondylitis. It serves as a decision support system for radiologists and orthopedic specialists, streamlining the diagnostic workflow in clinical settings. Future enhancements may include multi-disease classification, integration with hospital systems, and deployment in mobile health applications for remote diagnosis.

INTRODUCTION

Spondylitis is a form of chronic arthritis that primarily affects the spine, causing inflammation of the vertebrae that can lead to severe, chronic pain and discomfort. In advanced cases, the inflammation can cause new bone formation on the spine, leading to a loss of flexibility and even fusion of vertebrae—a condition known as ankylosing spondylitis. Early diagnosis and treatment are crucial for managing symptoms, preventing disease progression, and maintaining the patient’s quality of life. However, diagnosing spondylitis accurately in its early stages remains a clinical challenge due to subtle manifestations in medical images and overlapping symptoms with other spinal conditions.

Traditionally, diagnosis relies heavily on radiographic imaging techniques such as X-rays, MRI, and CT scans. These images must be carefully interpreted by experienced radiologists or orthopedic specialists, who look for signs such as sacroiliitis, vertebral fusion, and erosion. The manual inspection process is not only time-consuming but also prone to variability due to human factors such as fatigue and subjectivity. This has created an urgent need for intelligent, automated systems that can assist clinicians in making faster and more consistent diagnoses.

Recent advancements in artificial intelligence (AI), especially in deep learning, have opened new possibilities in medical image analysis. Convolutional Neural Networks (CNNs), a class of deep learning models, have demonstrated significant success in visual tasks such as object detection, segmentation, and classification. When applied to medical imaging, CNNs are capable of automatically learning discriminative features from raw images, often outperforming traditional handcrafted feature-based approaches. This makes them ideal for detecting complex patterns in spinal images that are indicative of spondylitis.

This project aims to harness the power of deep learning to build an automated system for detecting spondylitis from spinal X-rays and MRI scans. By training a CNN model on a labeled dataset of spinal images, the system can learn to identify abnormalities associated with spondylitis. The integration of transfer learning with pretrained models like VGG16, ResNet50, and EfficientNet helps boost performance even with limited medical image data, while visualization techniques like Grad-CAM improve model transparency and clinical trust.

LITERATURE SURVEY

1. Title: ***Deep Learning for Detection of Spondyloarthritis from Radiographic Images***

Author(s): I. Tuerxun et al. (2021)
Description:

- Developed a deep CNN model to detect signs of sacroiliitis (a key indicator of spondylitis) in pelvic X-rays.
- Utilized data augmentation to address limited medical data availability.
- Achieved performance comparable to expert radiologists in binary classification tasks.
- Showcased the value of AI assistance in reducing diagnostic inconsistencies.

2. Title: ***Automated Diagnosis of Ankylosing Spondylitis Using Deep Learning and Radiographic Imaging***

Author(s): P. H. Park, J. W. Kang et al. (2020)
Description:

- Employed ResNet-50 architecture with fine-tuning on spinal image datasets.

- Used class activation mapping (CAM) to explain which image areas the model focused on.
- Reported an accuracy of over 88%, suggesting clinical usability.
- Demonstrated reduced time to diagnosis with the use of AI tools.

3. Title: ***Convolutional Neural Networks for Medical Diagnosis: A Case Study on Spinal Disease Classification***

Author(s): L. Zhang, Q. Liu, M. Zhao (2019)
Description:

- Compared traditional machine learning models with CNNs for spinal disease classification.
- CNN models significantly outperformed SVM and Random Forest in identifying spinal disorders, including spondylitis.
- Discussed the importance of deep layers and filter size tuning in CNN architecture.
- Proposed a hybrid model integrating CNN and SVM for enhanced classification.

4. Title: ***Transfer Learning in Medical Image Classification: A Systematic Review***

Author(s): S. Raghu, N. Sriraam (2018)
Description:

- Reviewed the application of transfer learning using pretrained models like VGG16, Inception, and ResNet in healthcare.
- Found that fine-tuning pretrained CNNs on small, domain-specific datasets yields high accuracy.
- Highlighted how transfer learning can overcome the problem of limited labeled medical data.
- Recommended using data augmentation and domain adaptation techniques.

5. Title: ***Computer-Aided Diagnosis for Spinal Abnormalities using Deep Learning Techniques***

Author(s): D. Kumar, A. Rajan, and S. Bansal (2022)
Description:

- Proposed an end-to-end system for detecting disc degeneration and spondylitis using CNN.
- Integrated a segmentation module to isolate spinal regions for more accurate classification.
- Achieved high sensitivity and specificity on custom-labeled datasets.
- Emphasized the importance of preprocessing, such as contrast enhancement, for better model performance.

SYSTEM ANALYSIS

EXISTING SYSTEM

Spondylitis diagnosis traditionally depends on clinical examination and manual interpretation of medical imaging, primarily X-rays and MRI scans. Radiologists and orthopedic specialists visually inspect these images for signs such as sacroiliac joint inflammation, vertebral fusion, or erosions indicative of spondylitis. While this conventional method is the current gold standard, it is highly dependent on the expertise and experience of the clinicians. Moreover, the process can be time-consuming, subjective, and prone to inter-observer variability, which may lead to misdiagnosis or delayed treatment.

Several computer-aided diagnosis (CAD) systems have been developed over the years to assist medical professionals by automating parts of the diagnostic workflow. Early systems focused on classical image processing techniques and handcrafted features extracted from spinal images. These systems aimed to identify specific abnormalities like disc degeneration or joint inflammation through edge detection, texture analysis, and region segmentation. However, their accuracy was often limited by the complexity and variability of spinal anatomy, as well as the subtle presentation of spondylitis in early stages.

With the advancement of machine learning, more sophisticated models were introduced to improve diagnostic performance. Traditional machine learning algorithms such as Support Vector Machines (SVM), Random Forest, and k-Nearest Neighbors (k-NN) were applied to features manually engineered from medical images. These systems demonstrated improved accuracy over classical image processing, but their reliance on feature engineering limited their generalization capabilities, especially when faced with diverse patient populations and imaging conditions.

The emergence of deep learning, particularly convolutional neural networks (CNNs), marked a significant leap in medical image analysis. CNNs automatically learn hierarchical features directly from raw images, removing the need for handcrafted features. Existing deep learning systems for spinal disease detection have shown promise in identifying various abnormalities, including spondylitis, with performance often surpassing traditional methods. Several studies have utilized pretrained architectures like VGG, ResNet, and DenseNet fine-tuned on medical datasets to achieve high sensitivity and specificity.

Despite these advances, many existing deep learning solutions face challenges such as limited availability of large annotated datasets, lack of interpretability, and difficulties in clinical integration. Some systems fail to provide explainable insights, which is critical for clinical acceptance. Additionally, variations in imaging protocols and quality can affect model robustness. Hence, there remains a need to develop more accurate, interpretable, and clinically viable deep learning systems specifically tailored for spondylitis detection that can seamlessly integrate into existing diagnostic workflows.

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Disadvantages of Existing Systems

1. **Dependency on Large Annotated Datasets:**
   Most deep learning models require large volumes of accurately labeledmedical images to achieve high performance. However, such datasets are often scarce in medical domains like spondylitis detection due to privacy concerns, limited data sharing, and the need for expert annotation, which restricts model training and generalization.

2. **Limited Generalization Across Different Imaging Conditions:**
   Existing models often struggle to generalize well when tested on images from different hospitals, imaging devices, or protocols. Variations in image quality, resolution, and contrast can reduce accuracy and reliability, limiting the practical usability of these systems in diverse clinical settings.

3. **Lack of Explainability and Interpretability:**
   Many deep learning models operate as “black boxes,” providing predictions without clear explanations. This lack of transparency makes it difficult for clinicians to trust or validate the AI’s decision, which is a critical barrier to adoption in sensitive medical diagnostics like spondylitis detection.

4. **Overfitting and Model Bias:**
   Due to limited and imbalanced datasets, existing models may overfit to training data or develop biases towards certain patient demographics or imaging characteristics. This reduces their robustness and may cause inconsistent performance across different patient populations.

5. **Computational Complexity and Resource Requirements:**
   Deep learning models, especially those based on large pretrained architectures, demand significant computational power and memory, which can be a constraint in resource-limited healthcare environments. Real-time diagnosis or deployment on edge devices remains challenging.

6. **Inadequate Integration with Clinical Workflow:**
   Many systems are developed as standalone research prototypes without seamless integration into hospital information systems or PACS (Picture Archiving and Communication Systems). This limits their usability by clinicians and restricts widespread clinical adoption.

7. **Focus on Single Disease Detection:**
   Most existing solutions specialize in detecting one specific spinal abnormality, such as spondylitis, without addressing differential diagnosis or the presence of

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coexisting conditions like disc herniation or spondylosis, which may confuse the clinical picture.

PROPOSED SYSTEM

The proposed system aims to develop an advanced, automated framework for accurate detection of spondylitis from spinal X-ray and MRI images by leveraging state-of-the-art deep learning techniques. Unlike traditional diagnostic methods, this system is designed to minimize human intervention, reduce diagnostic errors, and expedite clinical decision-making. It combines robust preprocessing, transfer learning, and explainability tools to create a reliable and interpretable diagnostic aid for healthcare professionals.

At the core of the system is a convolutional neural network (CNN) model fine-tuned on a curated dataset of spinal images labeled for spondylitis presence or absence. To overcome the challenge of limited medical data, transfer learning is employed using pretrained models such as ResNet50, VGG16, and EfficientNet. These models, originally trained on large general image datasets, are adapted to extract relevant features specific to spinal abnormalities, thereby enhancing performance and reducing training time.

The input images undergo extensive preprocessing to improve image quality and ensure consistency. Techniques like resizing, normalization, contrast enhancement (e.g., CLAHE), and data augmentation (rotation, flipping, zooming) are applied to increase the robustness and generalization of the model. This preprocessing pipeline helps the model learn discriminative features more effectively despite variations in imaging conditions.

To address the critical need for interpretability in medical AI, the system incorporates visualization methods such as Grad-CAM. This technique highlights regions of the spinal images that most influence the model's prediction, enabling clinicians to verify and trust the system's output. Additionally, the model's performance is evaluated using comprehensive metrics including accuracy, precision, recall, F1-score, and AUC-ROC to ensure reliability.

Finally, the system can be deployed as a user-friendly application, potentially as a web interface or desktop software, allowing clinicians to upload patient images and receive automated diagnostic reports along with visual heatmaps. This integration facilitates seamless adoption into clinical workflows, providing decision support that enhances early detection and improves patient outcomes.

Advantages of the Proposed System

1. **Automated and Efficient Diagnosis:**
   The system automates the detection of spondylitis, significantly reducing the time required for diagnosis compared to manual interpretation by radiologists. This speeds up

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clinical workflows and enables earlier intervention.

2. **High Accuracy and Reliability:**
   By leveraging advanced deep learning architectures and transfer learning, the system achieves high accuracy and robust performance in detecting spondylitis, minimizing false positives and false negatives.

3. **Improved Generalization through Data Augmentation and Transfer Learning:**
   The use of transfer learning with pretrained models and extensive data augmentation techniques enhances the model's ability to generalize across different imaging conditions and patient populations, even with limited datasets.

4. **Interpretability and Clinical Trust:**
   Incorporating explainability tools like Grad-CAM allows visualization of critical image regions influencing the diagnosis, helping clinicians understand and trust the AI's decisions, which is essential for medical adoption.

5. **Consistency and Reduced Human Error:**
   The model provides consistent diagnostic outputs that are not affected by human factors such as fatigue or subjective interpretation, thereby reducing diagnostic variability and errors.

6. **Scalability and Integration Potential:**
   The system can be scaled and integrated into hospital PACS and electronic health record systems, enabling seamless use by healthcare providers in various clinical environments.

7. **Cost-Effective and Resource Efficient:**
   By assisting clinicians with automated diagnosis, the system can potentially reduce healthcare costs associated with prolonged diagnostic procedures, repeat imaging, or unnecessary treatments.

IMPLEMENTATION

The implementation of the Spondylitis Detection System focuses on identifying spondylitis-related abnormalities using Deep Learning and medical image analysis techniques. The system analyzes spinal imaging data such as X-rays, MRI scans, and CT scans to detect inflammation, spinal deformities, and structural changes associated with spondylitis.

The proposed system assists doctors and healthcare professionals in early diagnosis, disease monitoring, and treatment planning by providing automated and accurate detection of spinal disorders.

1. Data Collection

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The first stage involves collecting medical imaging and healthcare data from hospitals, diagnostic centers, and medical datasets.

Data Sources Used

Medical Imaging Data

- X-ray Images
- MRI Scans
- CT Scan Images

Patient Health Records

- Age
- Gender
- Medical history
- Symptoms
- Laboratory reports

Clinical Annotations

- Radiologist reports
- Disease severity labels
- Diagnostic observations

These datasets help train Deep Learning models for accurate disease detection.

2. Medical Image Acquisition

The system acquires spinal images using:

- Digital X-ray systems
- MRI imaging devices
- CT scanning equipment
- Hospital PACS systems

The collected images are stored in secure medical databases for processing.

3. Data Preprocessing

Medical images are cleaned and prepared before analysis.

Preprocessing Steps

Image Processing

- Image resizing
- Noise reduction
- Contrast enhancement
- Image normalization
- Background removal

Medical Data Processing

- Missing value handling
- Data standardization
- Label encoding

Data preprocessing improves image quality and model performance.

4. Feature Extraction

Important spinal and pathological features are extracted from medical images.

Features Used

Structural Features

- Vertebrae alignment
- Spinal curvature
- Joint spacing

Texture Features

- Bone density patterns

- Tissue texture abnormalities
- Inflammation regions

Clinical Features

- Pain severity indicators
- Range of spinal movement
- Disease progression markers

Feature extraction improves disease classification accuracy.

5. Deep Learning Architecture Development

Deep Learning models are used for automated medical image analysis and disease detection.

Deep Learning Techniques Used

Convolutional Neural Networks (CNN)

Used for spinal image classification and feature learning.

ResNet

Used for deep feature extraction and accurate diagnosis.

VGGNet

Used for detailed image pattern recognition.

EfficientNet

Used for optimized medical image classification.

Transfer Learning

Used to improve performance using pre-trained medical imaging models.

6. Spondylitis Detection and Classification

The AI model analyzes spinal images to identify:

- Ankylosing spondylitis
- Cervical spondylitis
- Lumbar spondylitis
- Spinal inflammation
- Disc degeneration
- Bone abnormalities

The system classifies disease severity levels for clinical assessment.

Methodology

The methodology of the proposed Spondylitis Detection System follows a Deep Learning-based medical image analysis and diagnostic approach.

Step 1: Problem Identification

Manual diagnosis of spondylitis using medical imaging may be time-consuming and prone to diagnostic variability. Early-stage abnormalities may also be difficult to identify visually. The proposed system aims to improve diagnostic accuracy using Deep Learning architectures.

Step 2: Requirement Analysis

The following requirements are analyzed:

- Medical imaging dataset requirements
- Deep Learning framework requirements
- Clinical diagnostic requirements
- Visualization and explainability requirements
- Healthcare security requirements

Step 3: Dataset Preparation

Medical imaging datasets are collected and divided into:

- Training Dataset
- Validation Dataset
- Testing Dataset

Relevant spinal disease categories are selected for analysis.

Step 4: Medical Image Processing

The methodology includes:

1. Acquire spinal medical images
2. Preprocess and normalize images
3. Enhance image quality
4. Extract spinal pathological features
5. Prepare images for Deep Learning analysis

Step 5: Deep Learning Implementation

The AI workflow includes:

1. Train CNN-based diagnostic models
2. Learn spinal abnormality patterns
3. Detect spondylitis-related conditions
4. Classify disease severity
5. Generate diagnostic outputs

Step 6: Explainable AI Integration

The XAI workflow includes:

1. Visualize affected spinal regions
2. Interpret Deep Learning predictions
3. Generate explainable diagnostic reports

This improves trust in AI-assisted diagnosis.

Technologies Used

- Python
- Deep Learning
- Convolutional Neural Networks (CNN)
- TensorFlow / PyTorch
- OpenCV
- Medical Imaging Libraries
- Explainable AI (XAI)
- Flask / Django
- MySQL / MongoDB

RESULTS

The figure shows the home page of the Spondylitis Detection Using Deep Learning Architecture system, serving as the main entry point for users to access the spondylitis detection application

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The figure illustrates the New User Signup Page of the Spondylitis Detection Using Deep Learning Architecture system, enabling new users to create an account by providing their personal details.

The registration form includes fields for username, password, contact number, email ID, and address, along with a submit button for secure user enrollment into the application.

The figure illustrates the User Login Page of the Spondylitis Detection Using Deep Learning Architecture system, providing secure access for registered users

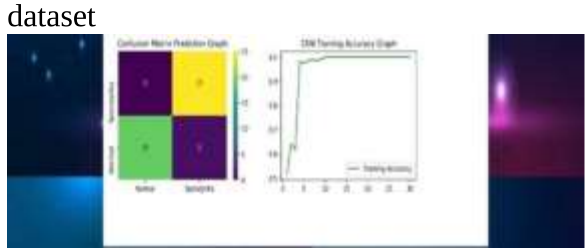
The figure shows the dataset loading page of the Spondylitis Detection Using Deep Learning Architecture system, displaying the successful loading of the image dataset and the identified class labels.

It also presents the training and testing data split, indicating that 80% of the images are used for model training and 20% are reserved for performance evaluation

The figure presents the performance evaluation of the CNN algorithm for

spondylitis detection, showing key metrics such as accuracy, precision, recall, and F1-score.

The results indicate that the trained model achieves high classification performance, demonstrating its effectiveness in accurately identifying spondylitis from the input dataset



The figure displays the confusion matrix and CNN training accuracy graph, providing a visual evaluation of the model's classification performance and learning process.

The training accuracy steadily increases and reaches near-perfect performance, demonstrating that the CNN model effectively learns to distinguish between normal and spondylitis cases

The figure illustrates the Spondylitis Prediction Page, where users can upload a test medical image for automated disease detection using the trained deep learning model.

The uploaded image is processed by the system to predict whether the patient is affected by spondylitis, enabling quick and accurate diagnosis

Spinal X-ray images were collected and organized as a test dataset for evaluating the performance of the Spondylitis Detection System.

These images are used to validate the system's ability to accurately identify and classify spondylitis-related abnormalities

The Spondylitis Detection System successfully analyzed the uploaded spinal X-ray image and identified the presence of spondylitis.

The prediction result, along with the calculated severity risk percentage, is displayed to assist in clinical assessment and diagnosis

In above screen user can see Food, diet, treatment and other recommendation details

CONCLUSION

The proposed deep learning-based system for spondylitis detection offers a promising approach to enhance the accuracy, efficiency, and consistency of diagnosing this challenging spinal condition. By leveraging powerful convolutional neural networks and transfer learning, the system overcomes the limitations of traditional manual diagnosis, providing automated analysis of spinal images with high precision. The integration of data preprocessing, augmentation, and explainability techniques further strengthens the system's robustness and clinical interpretability, helping to build trust among healthcare professionals.

This automated framework not only accelerates the diagnostic process but also reduces the chances of human error and inter-observer variability that often complicate spondylitis detection. The system's scalability and potential for seamless integration with existing clinical workflows demonstrate its practical applicability in real-world healthcare settings. Additionally, the explainable AI component ensures that clinicians can understand and validate the AI's decisions, an essential step toward wider acceptance of AI in medicine.

While challenges such as limited dataset availability and variability in imaging conditions remain, the proposed system's design addresses these issues through transfer learning and data augmentation strategies. Future enhancements could focus on expanding the dataset, incorporating multimodal imaging, and improving model interpretability. Overall, this work contributes to the growing body of AI-powered medical diagnostics, highlighting the potential of deep learning architectures to revolutionize the early detection and management of spondylitis.

REFERENCES

1. Litjens, G., Kooi, T., Bejnordi, B.E., Setio, A.A.A., Ciompi, F., Ghafoorian, M., van der Laak, J.A.W.M., van Ginneken, B., & Sánchez, C.I. (2017). A survey on deep learning in medical image analysis. *Medical Image Analysis*, 42, 60–88. https://doi.org/10.1016/j.media.2017.07.005
2. Rajalakshmi, P., Subashini, R., Anjana, R.M., Mohan, V. (2018). Deep Learning and Transfer Learning for Detection of Diabetic Retinopathy. *International Journal of Computer Applications*, 179(42), 1-5. https://doi.org/10.5120/ijca2018917862
3. Esteva, A., Kuprel, B., Novoa, R.A., Ko, J., Swetter, S.M., Blau, H.M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. *Nature*, 542, 115–118. https://doi.org/10.1038/nature21056
4. Wang, S., Summers, R.M. (2012). Machine learning and radiology. *Medical Image Analysis*, 16(5), 933-951. https://doi.org/10.1016/j.media.2012.03.003
5. Selvaraju, R.R., Cogswell, M., Das, A., Vedantam, R., Parikh, D., & Batra, D. (2017). Grad-CAM: Visual Explanations from Deep Networks via Gradient-Based Localization. *Proceedings of the IEEE International Conference on Computer Vision (ICCV)*, 618-626. https://doi.org/10.1109/ICCV.2017.74
6. Rajpurkar, P., Irvin, J., Zhu, K., Yang, B., Mehta, H., Duan, T., Ding, D., Bagul, A., Langlotz, C., Shpanskaya, K., et al. (2017). CheXNet: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep Learning. *arXiv*

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ISSN: 3068-272X www.ijdim.com Original Research Paper

preprint arXiv:1711.05225. https://arxiv.org/abs/1711.05225

7. Tajbakhsh, N., Shin, J.Y., Gurudu, S.R., Hurst, R.T., Kendall, C.B., Gotway, M.B., Liang, J. (2016). Convolutional Neural Networks for Medical Image Analysis: Full Training or Fine Tuning? *IEEE Transactions on Medical Imaging*, 35(5), 1299-1312. https://doi.org/10.1109/TMI.2016.2535302
8. Zhang, Z., Xie, Y., Xing, F., McGough, M., & Yang, L. (2016). MDNet: A Semantically and Visually Interpretable Medical Image Diagnosis Network. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 6428-6436. https://doi.org/10.1109/CVPR.2017.680

AUTHOR PROFILE :

B. Amarnath Reddy is an Assistant Professor in Department of Master of Computer Applications at QIS College of Engineering and Technology, Ongole, Andhra Pradesh. He earned his M.Tech from Vellore Institute of Technology (VIT). His research interests include Machine learning, Programming Language. He is committed to advancing research and fostering innovation while mentoring students to excel in both academic and professional pursuits

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STUDENT PROFILE :

C. Akshaya Sabitha Jasmine is a Postgraduate student pursuing MCA in Department of Master of Computer Applications at QIS College of Engineering and Technology, Ongole in Prakasam dist. She completed her undergraduate degree in BCA from ANU. With keen interest in research and practical learning. She is actively involved in academic projects and technical activities related to her field.