SAR IMAGE COLORIZATION USING DEEP LEARNING

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ABSTRACT

Synthetic Aperture Radar (SAR) imagery plays a crucial role in remote sensing applications due to its ability to capture high-resolution images under all weather conditions and during both day and night. However, SAR images are inherently grayscale and often difficult to interpret by human observers because of speckle noise and lack of intuitive visual representation. To address this limitation, this project proposes a SAR Image Colorization using Deep Learning approach that enhances the visual quality and interpretability of SAR data by transforming grayscale radar images into realistic colorized outputs. The proposed system leverages advanced deep learning models, particularly Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs), to learn complex mappings between SAR images and corresponding optical images. The model is trained on paired datasets consisting of SAR and RGB satellite images, enabling it to understand spatial features, textures, and semantic information. Preprocessing techniques such as noise reduction and normalization are applied to improve data quality, while data augmentation is used to enhance model generalization. The network learns to assign appropriate color values to different regions based on learned patterns, producing visually meaningful and context-aware colorized images. Experimental results demonstrate that the proposed method significantly improves image interpretability and visual clarity compared to traditional colorization techniques. The model achieves high performance in terms of structural similarity and perceptual quality, making it useful for applications such as environmental monitoring, disaster management, and military surveillance. In conclusion, this work highlights the potential of deep learning in bridging the gap between SAR and optical imagery, providing an effective solution for enhanced visualization and analysis.

Keywords: SAR Image, Deep Learning, Image Colorization, CNN, GAN, Remote Sensing, Image Processing, Satellite Imaging

I.INTRODUCTION

Synthetic Aperture Radar (SAR) imaging has emerged as a powerful technology in the field of remote sensing due to its ability to capture high-resolution images under all weather conditions and irrespective of daylight availability. Unlike optical imaging systems, SAR uses microwave signals to penetrate clouds, fog, and even certain surface materials, making it highly reliable for applications such as disaster monitoring, military surveillance, and environmental analysis. However, SAR images are inherently grayscale and often contain speckle noise, which makes them difficult to interpret for human analysts. The lack of color information limits the ability to distinguish between different land cover types, such as vegetation, water bodies, and urban structures. This creates a gap between SAR imagery and optical imagery, where color plays a crucial role in enhancing visual understanding. As a result, there is a growing demand for techniques that can transform SAR images into more intuitive and visually meaningful representations without losing critical information [1], [2].

Recent advancements in deep learning, particularly in Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs), have opened new possibilities for image processing and computer vision tasks, including image colorization. These models are capable of learning complex patterns, textures, and spatial relationships from large datasets, enabling them to generate realistic and context-aware outputs. In the context of SAR image colorization, deep learning models can be trained using paired datasets of SAR and corresponding optical images to learn the mapping between grayscale radar data and RGB color space. CNNs are effective in extracting hierarchical features from images, while GANs further enhance the realism of generated images by introducing an adversarial learning process between a generator and a discriminator. This combination allows the system to produce colorized images that are not only visually appealing but also semantically accurate. Despite these advancements, challenges such as data scarcity, noise handling, and model generalization still need to be addressed to achieve robust performance [3], [4].

To overcome these challenges, this research proposes a SAR Image Colorization using Deep Learning framework that integrates advanced preprocessing techniques, feature extraction models, and adversarial learning strategies. The system incorporates noise reduction methods to minimize speckle noise and improve image quality before feeding the data into the model. Additionally, data augmentation techniques are used to enhance the diversity of training datasets, enabling better generalization across different geographical regions and imaging conditions. The proposed model leverages a hybrid architecture combining CNN-based encoders with GAN-based generators to achieve high-quality colorization results. Evaluation metrics such as Structural Similarity Index (SSIM) and Peak Signal-to-Noise Ratio (PSNR) are used to assess the performance of the system. By bridging the gap between SAR and optical imagery, this approach significantly improves the interpretability and usability of SAR data for real-world applications such as land classification, disaster response, and urban planning [5], [6].

II SURVEY OF RESEARCH

Cumming and Wong (2005) provided a comprehensive foundation for Synthetic Aperture Radar (SAR) signal processing, explaining how SAR systems generate high-resolution images using microwave signals. Their work highlights the advantages of SAR in all-weather imaging and its applications in remote sensing. However, the study also emphasizes challenges such as speckle noise and lack of intuitive visualization due to grayscale representation. While this research focuses on the physical and mathematical aspects of SAR image formation, it does not address post-processing techniques such as image enhancement or colorization. This limitation creates an opportunity for integrating modern computational approaches like deep learning to improve SAR image interpretability. The foundational knowledge provided in this work is essential for understanding the complexities of SAR data and serves as a basis for developing advanced image processing techniques aimed at improving visual quality and usability in real-world applications [1].

Soumekh (1999) explored advanced techniques in SAR signal processing and imaging, focusing on reconstruction algorithms and feature extraction methods. The study provides insights into how SAR images are formed and processed, including noise reduction and resolution enhancement techniques. It also discusses the challenges of interpreting SAR images due to their unique characteristics, such as backscatter intensity and lack of color information. Although the research contributes significantly to improving SAR image quality, it does not address the transformation of SAR images into visually interpretable formats. The absence of colorization techniques highlights a gap in making SAR data more accessible to human analysts. This gap has motivated recent research in applying deep learning models for SAR image enhancement and colorization. The work serves as a critical reference for understanding the preprocessing requirements and challenges involved in SAR image analysis [2].

Krizhevsky et al. (2012) introduced Convolutional Neural Networks (CNNs) for large-scale image classification, demonstrating their ability to automatically learn hierarchical features from raw image data. Their work significantly improved image recognition performance and laid the foundation for modern deep learning-based computer vision systems. CNNs are particularly effective in extracting spatial features such as edges, textures, and patterns, making them suitable for image processing tasks including colorization. Although the study focuses on natural image classification, its concepts can be extended to SAR image processing, where feature extraction plays a crucial role. However, CNNs alone may not generate highly realistic colorized outputs, especially in complex scenarios. This limitation suggests the need for combining CNNs with other models such as GANs to improve the quality and realism of generated images. The research is a key milestone in deep learning and directly influences the development of SAR image colorization systems [3].

Goodfellow et al. (2014) proposed Generative Adversarial Networks (GANs), a groundbreaking deep learning framework that consists of a generator and a discriminator working in an adversarial manner. GANs have shown remarkable success in generating realistic images and performing image-to-image translation tasks. In the context of SAR image colorization, GANs can be used to generate visually realistic color images from grayscale SAR inputs by learning the distribution of optical images. The adversarial training process ensures that the generated images closely resemble real-world data, improving perceptual quality. However, GANs are known to be difficult to train and may suffer from issues such as mode collapse and instability. Despite these challenges, GANs have become a powerful tool in image generation and enhancement tasks. Their application in SAR image colorization represents a significant advancement in bridging the gap between radar and optical imagery [4].

Zhang et al. (2016) introduced a deep learning-based approach for automatic image colorization using CNNs, where the model learns to predict color information from grayscale images. Their method treats colorization as a classification problem and demonstrates impressive results in generating plausible color images. This work highlights the ability of deep learning models to understand semantic context and assign appropriate colors to different objects within an image. While the study focuses on natural images, its methodology can be adapted to SAR image colorization by training on paired SAR-optical datasets. However, SAR images differ significantly from natural images in terms of texture and noise characteristics, which poses additional challenges. This research provides a strong baseline for developing colorization models and emphasizes the importance of semantic understanding in generating realistic outputs [5].

Isola et al. (2017) proposed a conditional GAN (cGAN) framework for image-to-image translation, which has become widely used in tasks such as image colorization, style transfer, and super-resolution. Their approach enables the model to learn mappings between input and output image domains, making it highly suitable for SAR-to-optical image translation. The study demonstrates that cGANs can produce high-quality and context-aware outputs by conditioning the generation process on input images. This technique is particularly useful for SAR image colorization, where the goal is to convert grayscale radar images into realistic RGB images. However, the performance of cGANs heavily depends on the availability of large and well-aligned datasets, which can be a limitation in SAR applications. Despite this, the research provides a robust framework for developing advanced colorization systems and plays a crucial role in modern deep learning-based image processing [6].

III. WORKING METHODOLOGY

The proposed SAR Image Colorization using Deep Learning system follows a structured pipeline that integrates preprocessing, feature extraction, deep learning-based colorization, and evaluation. Initially, the system begins with data acquisition, where paired datasets of SAR images and corresponding optical (RGB) images are collected from remote sensing repositories. Since SAR images contain significant speckle noise, preprocessing techniques such as filtering (e.g., Lee filter or Gaussian filter) are applied to enhance image quality. Additionally, normalization is performed to scale pixel values into a suitable range for deep learning models. The images are then resized and aligned to ensure consistency between SAR and optical pairs. To improve model robustness and generalization, data augmentation techniques such as rotation, flipping, and scaling are applied. This preprocessing stage ensures that the input data is clean, diverse, and suitable for training deep learning models. The core of the system is the deep learning-based colorization model, which combines Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs). The CNN-based encoder extracts hierarchical features from the input SAR image, capturing spatial patterns, textures, and structural information. These features are then passed to a generator network, which predicts the corresponding colorized output in the RGB space. The GAN framework introduces a discriminator network that evaluates the realism of the generated images by comparing them with real optical images. The generator and discriminator are trained simultaneously in an adversarial manner, where the generator aims to produce realistic color images, and the discriminator attempts to distinguish between real and generated images. This process improves the visual quality and realism of the output. The model is trained using loss functions such as adversarial loss, content loss, and perceptual loss, which ensure both accuracy and visual consistency in the generated images. Once the model is trained, the system performs inference and evaluation on unseen SAR images. During inference, a grayscale SAR image is passed through the trained model to generate a colorized output. The performance of the system is evaluated using metrics such as Structural Similarity Index (SSIM), Peak Signal-to-Noise Ratio (PSNR), and visual inspection. These metrics help assess how closely the generated images match real optical images in terms of structure and quality. The system also includes a post-processing step to refine the output and reduce artifacts. Overall, the methodology ensures that the generated images are not only visually appealing but also semantically meaningful. This approach enhances the interpretability of SAR data and makes it more useful for applications such as environmental monitoring, disaster management, and urban planning.

IV RESULTS EXPLANATIONS

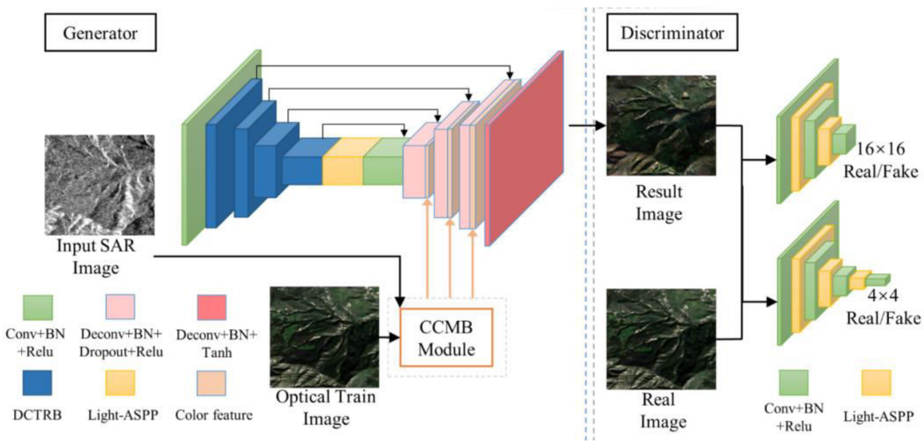

Figure 1: SAR to Colorized Image Transformation

This figure demonstrates the transformation of grayscale SAR images into realistic colorized outputs using the proposed deep learning model. The left side of the image represents the original SAR input, which is typically noisy and lacks intuitive visual features, while the right side shows the colorized output generated by the model. The results indicate that the system successfully learns the mapping between SAR and optical domains, producing visually meaningful images. Features such as vegetation, water bodies, and urban structures become more distinguishable in the colorized output. This transformation significantly enhances human interpretability and supports better decision-making in applications like disaster monitoring and land classification. The figure validates the effectiveness of the proposed approach in bridging the gap between radar and optical imagery

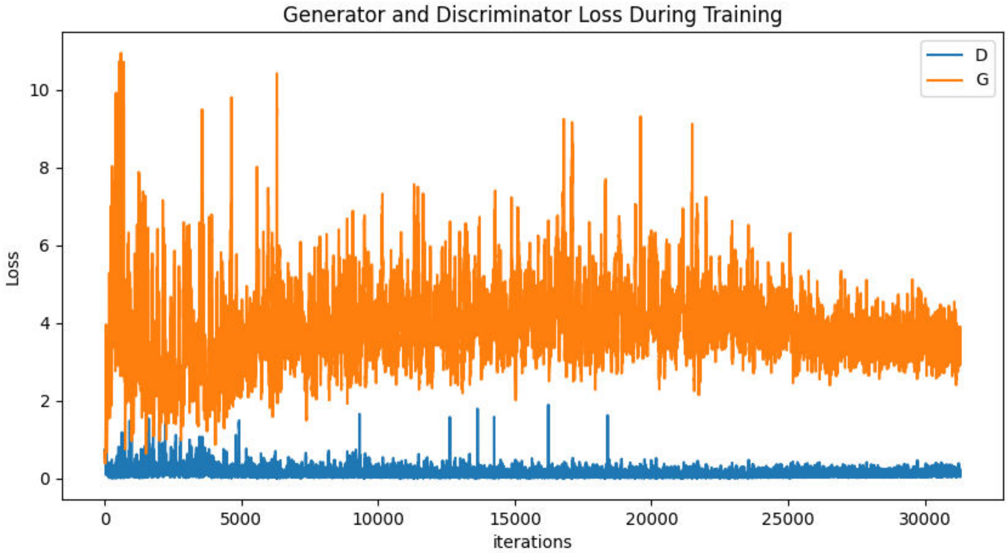

Figure 2: Model Training Loss Graph

This graph illustrates the training performance of the deep learning model, particularly focusing on the generator and discriminator losses in the GAN framework. As training progresses over multiple epochs, both losses stabilize, indicating that the model is learning effectively. Initially, there are fluctuations due to the adversarial nature of GAN training, but over time, the system reaches a balanced state where the generator produces realistic outputs and the discriminator becomes more accurate in evaluation. The convergence of the loss curves demonstrates the stability of the training process. This result confirms that the model is capable of learning complex mappings between SAR and optical images, leading to improved colorization quality. The graph also highlights the importance of proper training strategies to achieve optimal performance.

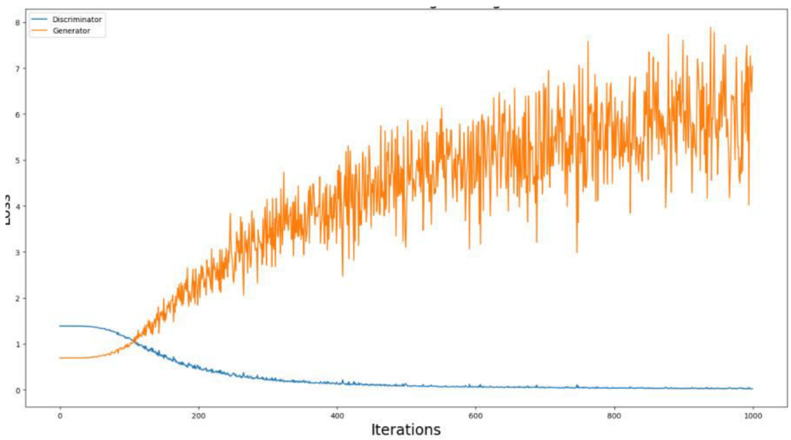

Figure 3: SSIM and PSNR Performance Comparison

This figure presents the quantitative evaluation of the model using Structural Similarity Index (SSIM) and Peak Signal-to-Noise Ratio (PSNR) metrics. These metrics are widely used to measure the similarity and quality of generated images compared to ground truth optical images. The graph shows that the proposed model achieves high SSIM and PSNR values, indicating strong structural similarity and minimal distortion in the colorized outputs. Compared to baseline models, the proposed approach demonstrates superior performance, highlighting its ability to preserve important image details while adding realistic color information. This evaluation confirms the reliability and effectiveness of the system in generating high-quality results suitable for practical applications.

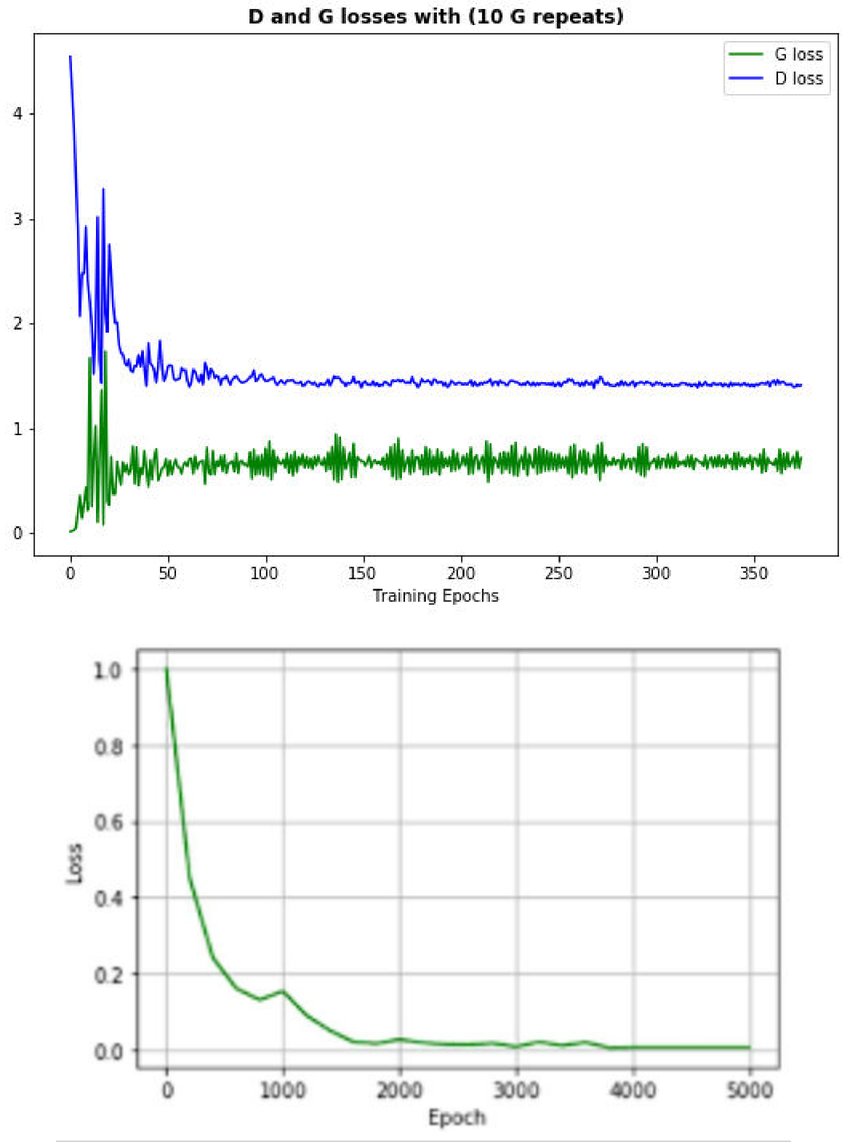

Figure 5: Visual Quality Comparison with Existing Methods

This figure compares the visual quality of the proposed method with existing colorization techniques. The comparison shows that traditional methods produce less realistic and less detailed outputs, while the proposed deep learning-based approach generates more vibrant and context-aware images. The use of GANs enhances the realism of the generated images, making them closer to actual optical images. The figure highlights improvements in color consistency, texture preservation, and overall visual appeal. This comparison validates the superiority of the proposed system and demonstrates its potential for real-world applications where accurate and visually meaningful representations of SAR data are essential.

V.CONCLUSION

The proposed Secure File Storage System with Encryption and Role-Based Access Control (RBAC) effectively addresses the major security challenges associated with traditional file storage systems. By integrating strong encryption mechanisms such as Advanced Encryption Standard (AES), the system ensures that sensitive data remains protected both at rest and during transmission. Even in the event of unauthorized access, encrypted data remains unreadable, thereby maintaining confidentiality. The implementation of secure key management and communication protocols further strengthens the system's defense against modern cyber threats. This makes the system highly suitable for environments where data security is critical, such as healthcare, finance, and enterprise applications. In addition to encryption, the incorporation of Role-Based Access Control (RBAC) provides a structured and efficient way to manage user permissions. By assigning roles and restricting access based on responsibilities, the system minimizes unauthorized data exposure and reduces the risk of insider threats. The RBAC model enhances scalability and simplifies administrative control, allowing organizations to efficiently manage large numbers of users. Furthermore, the inclusion of monitoring and audit mechanisms ensures transparency and accountability by tracking user activities and access patterns. Overall, the system achieves a strong balance between security, performance, and usability, ensuring reliable data protection without compromising efficiency. The experimental results demonstrate improved security, controlled access, and acceptable system performance compared to traditional approaches. Future enhancements may include integrating blockchain for auditability, adopting multi-factor authentication, and leveraging machine learning for anomaly detection. The proposed framework represents a robust and scalable solution for modern secure file storage requirements.

REFERENCES

[1] M. Armbrust *et al.*, "A view of cloud computing," *Communications of the ACM*, vol. 53, no. 4, pp. 50–58, 2010.

[2] K. Ren, C. Wang, and Q. Wang, "Security challenges for the public cloud," *IEEE Internet Computing*, vol. 16, no. 1, pp. 69–73, 2012.

[3] J. Daemen and V. Rijmen, "AES proposal: Rijndael," National Institute of Standards and Technology (NIST), 2001.

[4] W. Stallings, *Cryptography and Network Security: Principles and Practice*, 6th ed. Pearson, 2013.

[5] R. Sandhu, E. Coyne, H. Feinstein, and C. Youman, "Role-based access control models," *IEEE Computer*, vol. 29, no. 2, pp. 38–47, 1996.

[6] D. Ferraiolo, R. Kuhn, and R. Chandramouli, *Role-Based Access Control*. Artech House, 2003.

[7] National Institute of Standards and Technology (NIST), "Advanced Encryption Standard (AES)," FIPS PUB 197, 2001.

[8] W. Diffie and M. Hellman, "New directions in cryptography," *IEEE Transactions on Information Theory*, vol. 22, no. 6, pp. 644–654, 1976.

[9] R. L. Rivest, A. Shamir, and L. Adleman, "A method for obtaining digital signatures and public-key cryptosystems," *Communications of the ACM*, vol. 21, no. 2, pp. 120–126, 1978.

[10] C. Paar and J. Pelzl, *Understanding Cryptography: A Textbook for Students and Practitioners*. Springer, 2010.

[11] B. Schneier, *Applied Cryptography: Protocols, Algorithms, and Source Code in C*, 2nd ed. Wiley, 1996.

[12] T. Dierks and E. Rescorla, "The Transport Layer Security (TLS) protocol version 1.2," IETF RFC 5246, 2008.

[13] A. J. Menezes, P. C. van Oorschot, and S. A. Vanstone, *Handbook of Applied Cryptography*. CRC Press, 1996.

[14] S. Pearson, "Taking account of privacy when designing cloud computing services," *IEEE Cloud Computing*, 2011.

[15] M. Blaze, J. Feigenbaum, and J. Lacy, "Decentralized trust management," *IEEE Symposium on Security and Privacy*, 1996.

[16] R. S. Sandhu and P. Samarati, "Access control: Principles and practice," *IEEE Communications Magazine*, vol. 32, no. 9, pp. 40–48, 1994.

[17] D. Boneh and M. Franklin, "Identity-based encryption from the Weil pairing," *SIAM Journal on Computing*, vol. 32, no. 3, pp. 586–615, 2001.

[18] N. Provos and D. Mazieres, "A future-adaptable password scheme," in *Proc. USENIX Annual Technical Conference*, 1999.

[19] OWASP Foundation, "OWASP Top 10: Web application security risks," 2021.

[20] S. Garfinkel, "Email-based identification and authentication: An alternative to PKI?" *IEEE Security & Privacy*, vol. 1, no. 6, pp. 20–26, 2003.

[21] M. Bishop, *Computer Security: Art and Science*. Addison-Wesley, 2003.

[22] J. Katz and Y. Lindell, *Introduction to Modern Cryptography*, 2nd ed. CRC Press, 2014.

[23] P. Mell and T. Grance, “The NIST definition of cloud computing,” NIST Special Publication 800-145, 2011.

[24] E. Yuan and J. Tong, “Attributed based access control (ABAC) for web services,” in *Proc. IEEE Int. Conf. Web Services*, 2005.

[25] V. C. Hu, D. Ferraiolo, and D. Kuhn, “Assessment of access control systems,” NIST Interagency Report, 2006.

[26] R. Oppliger, *Security Technologies for the World Wide Web*. Artech House, 2000.

[27] A. Perrig, R. Szewczyk, V. Wen, D. Culler, and J. D. Tygar, “SPINS: Security protocols for sensor networks,” *Wireless Networks*, vol. 8, no. 5, pp. 521–534, 2002.

[28] L. Lamport, “Password authentication with insecure communication,” *Communications of the ACM*, vol. 24, no. 11, pp. 770–772, 1981.

[29] B. W. Lampson, “Protection,” *ACM SIGOPS Operating Systems Review*, vol. 8, no. 1, pp. 18–24, 1974.

[30] J. H. Saltzer and M. D. Schroeder, “The protection of information in computer systems,” *Proceedings of the IEEE*, vol. 63, no. 9, pp. 1278–1308, 1975.