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**Thesis Topic**

# Speckle filtering in SAR images using deep learning methods


**Supervised by:**

- Dr. Azmedroub Boussad.

**Submitted by:**

- Boufellah Amina.
- Rahma Nadjat.


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بِسْمِ اللَّهِ الرَّحْمَنِ الرَّحِيمِ

# إ ه د ا ء

بسم الله الرحمن الرحيم،

الحمد لله الذي وفقني و اعانني على إتمام هذه المذكرة. احمده سبحانه على عونه وتوفيقه الذي لولاه لما وصلت إلى هذا الإنجاز.

إلى افراد عائلتي الغالية، بوفالح وفنيط.

إلى إخواني و اخواتي من كانوا لي السند والدفء في كل خطوة خطوتها في حياتي، والدي الأعزاء، اشكركم على دعمكم اللامتناهي وتشجيعكم المستمر لي. هذا الإنجاز ثمرة صبركم ومحبتكم.

إلى زميلة دراستي، رحمة نجاة،

شكراً لك على المشاركة في كل لحظة من هذه الرحلة الأكاديمية، كنت لي الداعمة والصديقة في اصعب الاوقات.

الى رفيق دربي في مشوار الحياة والسند الأكبر لي، السيد زياد حوّاس.

إلى استاذي المشرف،

اقدم لك خالص التقدير والامتنان على توجيهاتك الحكيمة وإرشاداتك القيمة التي كانت الاساس في إنجاز هذا العمل. شكرا على صبرك ودعمك.

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مستقبلي ا

بوفالح امينة.

# إهداء وشكر

الحمد هلل اول واخ را الذي بفضله تمت هذه الرحلة. اشكر هللا على نعمه التي ال تعد وال تحصى، وعلى التوفيق والقوة التي منحني إياها.

إلى عائلتي العزيزة، التي كانت دائماً النور الذي يرشدني في لحظات الشك، والداعم الذي ال يكل وال يمل. إلى والدي الحبيبين، انتما النبع الذي استقيت منه قوة اإلرادة والعزيمة، والمالذ الذي الجأ إليه في كل حين بفضل حبكما، صبركما، وإيمانكما بي، استطعت ان ابلغ هذا الحد. كل ما انا عليه اليوم وما س اكون عليه في المستقبل، مدين به لكما.

وال انسى صديقتي العزيزة بوفالح امينة، التي كانت سندا خالل كل خطوة من هذه الرحلة. شكرا على وجودك الدائم وتشجيعك المستمر. لقد كنت خير رفيقة.

كما اود ان اعبر عن امتناني لزوج اختي، ريحي بلخير، الذي كان مثاال للدعم واالخوة الحقيقية. شكرا لوقوفك بجانبي ومساندتك لي.

و اتوجه بالشكر العميق إلى استاذي الفاضل، الذي قدم لي توجيهاته القيمة وكان دليال لي في هذه الرحلة.

رحمة نجاة.

## Abstract:

Synthetic Aperture Radar (SAR) imaging plays a crucial role in remote sensing applications due to its ability to capture high-resolution images regardless of weather conditions. However, SAR images are often affected by speckle noise, which hinders the visual quality and accuracy of subsequent analyses. This thesis focuses on the despeckling of SAR images using advanced deep learning techniques, with an emphasis on the Block-Matching 3D (BM3D) method.

We propose a deep learning framework that integrates the strengths of BM3D with modern neural network architectures to effectively reduce speckle noise while preserving image details and structural integrity. The proposed method is compared against traditional despeckling techniques in terms of performance metrics such as Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), and visual quality. Extensive experimentation on both synthetic and real-world SAR datasets demonstrates the superior performance of the proposed model, highlighting its potential for improving SAR image analysis in various remote sensing applications.

## Résumé :

L'imagerie par radar à synthèse d'ouverture (SAR) joue un rôle essentiel dans les applications de télédétection grâce à sa capacité à capturer des images haute résolution quelles que soient les conditions météorologiques. Cependant, les images SAR sont souvent affectées par le bruit de chatoiement, ce qui compromet la qualité visuelle et l'exactitude des analyses ultérieures. Cette thèse se concentre sur le débruitage des images SAR en utilisant des techniques avancées d'apprentissage profond, en mettant l'accent sur la méthode Block-Matching 3D (BM3D).

Nous proposons un cadre d'apprentissage profond qui intègre les forces du BM3D avec des architectures modernes de réseaux neuronaux pour réduire efficacement le bruit tout en préservant les détails et l'intégrité structurelle de l'image. La méthode proposée est comparée aux techniques traditionnelles de débruitage en termes de métriques de performance telles que le rapport signal sur bruit de pointe (PSNR), l'indice de similarité structurelle (SSIM) et la qualité visuelle. De nombreuses expérimentations sur des jeux de données SAR synthétiques et réels démontrent la performance supérieure du modèle proposé, soulignant son potentiel à améliorer l'analyse des images SAR dans diverses applications de télédétection.

## الملخص:

تلعب صور الرادار ذي الفتحة الاصطناعية (SAR) دوراً مهماً في تطبيقات الاستشعار عن بعد نظراً لقدرتها على التقاط صور عالية الدقة بغض النظر عن الظروف الجوية. ومع ذلك، غالباً ما تتأثر صور الـ SAR بضوضاء "الرقطة (Speckle)"، مما يؤثر سلباً على جودة الصورة ويعيق دقة التحليل اللاحق. تركز هذه المذكرة على إزالة ضوضاء الرقطة من صور الـ SAR باستخدام تقنيات التعلم العميق
المتقدمة، مع التركيز على طريقة (BM3D). "نقترح إطار عمل يعتمد على التعلم العميق يدمج بين طريقة BM3D وهياكل الشبكات العصبية الحديثة لتقليل ضوضاء الرقطة بفعالية مع الحفاظ على تفاصيل الصورة وسلامة بنيتها. يتم مقارنة الطريقة المقترحة مع تقنيات إزالة الضوضاء التقليدية من حيث مقاييس الأداء مثل نسبة الإشارة إلى الضوضاء (PSNR) ومؤشر قياس التشابه الهيكلي (SSIM) وجودة الصورة البصرية. اظهرت التجارب المكثفة على مجموعات بيانات SAR الاصطناعية والحقيقية للأداء المتفوق للنموذج المقترح، مما يعزز إمكانياته في تحسين تحليل صور الـ SAR في مختلف تطبيقات الاستشعار عن بعد.

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## GENERAL INTRODUCTION:

Synthetic Aperture Radar (SAR) is a form of radar used to create two-dimensional images or three-dimensional reconstructions of objects, such as landscapes. SAR systems are mounted on aircraft or satellites and can operate in various weather conditions and during both day and night. This capability makes SAR a powerful tool for a wide range of applications, including environmental monitoring, military surveillance, and disaster management.

SAR works by emitting microwave signals toward the Earth's surface and then receiving the signals that are reflected back. By processing these reflected signals, it is possible to generate high-resolution images. Unlike optical imaging systems, SAR is not limited by cloud cover or lack of daylight, making it an invaluable tool for continuous monitoring.

However, the unique characteristics of SAR imagery come with their own challenges. One significant issue is the presence of speckle noise, which is a granular noise that degrades the qualityof SAR images. Speckle noise is a result of the coherent nature of the radar signal and the constructive and destructive interference of the returned signal. This noise can obscure important features in the image, making it difficult to interpret and analyze the data accurately.

Speckle noise is a multiplicative noise that affects all coherent imaging systems, including SAR.It arises due to the random interference of the coherent waves scattered by the rough surface of the target. While speckle noise contains some information about the surface properties, it predominantly hampers the visual quality of the image and the performance of subsequent image processing tasks such as classification, segmentation, and change detection.

To mitigate the effects of speckle noise, various filtering techniques have been developed. These techniques aim to preserve the essential features and structures in the image while reducing the noise. One such advanced technique is Block-Matching and 3D Filtering (BM3D).

The primary motivation for this research is to improve the quality of SAR images by effectively reducing speckle noise. High-quality SAR images are crucial for accurate interpretation and analysis in various applications. Traditional speckle filtering techniques, such as Lee, Frost, and Gamma MAP filters, have limitations in terms of preserving fine details and edges in the image. Therefore, there is a need for more advanced filtering techniques that can offer better performance.

BM3D is a state-of-the-art denoising algorithm initially developed for optical images. Itleverages both local and non-local image properties to achieve superior noise reduction. The extension of BM3D to SAR images presents an opportunity to significantly enhance the quality ofSAR imagery.

The main objective of this research is to evaluate the effectiveness of the BM3D filtering technique for reducing speckle noise in SAR images. The specific goals include:

1. Implementation of BM3D for SAR Images: Adapt the BM3D algorithm to be suitable for SAR image processing.
2. Performance Evaluation: Assess the performance of BM3D in terms of speckle noise reduction and preservation of image details. This will involve quantitative measures such as Peak signal-to-NoiseRatio (PSNR), structural similarity (SSIM), and also qualitative assessment by visual inspection.
3. Comparison with Traditional Filters: Compare the results obtained from BM3D with those from traditional speckle filters to highlight the advantages and potential improvements.

By achieving these objectives, this thesis aims to demonstrate the utility of BM3D in enhancing SAR image quality and thereby support more accurate and reliable analysis of SAR data in practical applications.

# CHAPTER 1:

# INTRODUCTION TO SYNTHETIC APERTURE RADAR (SAR) AND SPECKLE PHENOMENA

# 1) Introduction:

The quest for high-resolution, reliable imaging technology that can operate effectively in all weather conditions and at any time of day has long been a challenge for researchers and engineers. Traditional optical and infrared imaging systems, while capable of providing detailed images, are severely limited by their dependence on clear skies and daylight. These limitations hinder continuous monitoring and data collection, especially in regions prone to persistent cloud cover, adverse weather, or during nighttime operations.

Additionally, conventional radar systems, which rely on the physical size of the antenna to determine resolution, face significant constraints. Achieving high resolution with these systems would require impractically large antennas, making them unsuitable for many airborne or spaceborne applications.

This limitation has prompted the need for an innovative approach that can deliver high-resolution imagery without the burdensome requirements of large physical structures.Another critical challenge is the need for wide-area coverage and frequent monitoring. Many applications, such as environmental monitoring, disaster management, and military surveillance, require extensive and repeated imaging of large regions.

Traditional imaging systems often fall short in providing the necessary spatial coverage and temporal resolution needed for these applications.Furthermore, obtaining detailed information about surface and structural properties is essential for various scientific and practical applications. Conventional imaging technologies struggle to provide insights into surface roughness, moisture content, and structural variations, which are crucial for geological studies, agricultural assessments, and infrastructure inspections.

To address these challenges, researchers developed Synthetic Aperture Radar (SAR) .

SAR leverages the motion of the radar platform to simulate a much larger antenna, achieving high-resolution imaging capabilities without the need for a large physical antenna. Operating in the microwave spectrum, SAR can penetrate clouds, rain, and function independently of sunlight, ensuring reliable imaging under all weather conditions and at any time of day. Its ability to cover large areas quickly and repeatedly makes it an invaluable tool for comprehensive and continuous monitoring.

# 2) Introduction to Synthetic Aperture Radar

## 2.1)Historical Development of Synthetic Aperture Radar

The development of Synthetic Aperture Radar (SAR) has its roots in the mid-20$^{th}$ century, emerging from the advancements in radar technology during World War II. The concept of SAR was introduced as a means to overcome the limitations of conventional radar systems, particularly their resolution capabilities.

The initial development phase began in the 1950s and 1960s when scientists and engineers sought to enhance radar imaging resolution by exploiting the relative motion between the radar platform and the target. This led to the conceptualization of the “synthetic aperture,” which is the effective length of the antenna created by the movement of the radar system. By processing the returned signals, it became possible to achieve much higher resolution images than those produced by real-aperture radar systems of the same physical antenna size. Early SAR systems were primarily developed for military applications, with the U.S. Department of Defense playing a significant role. The first success SAR system was flown on the Convair B-36 Peacemaker bomber in the late 1950s. These early systems demonstrated the feasibility of SAR but were limited by the analog technology of the time, which constrained the quality and usability of the radar images.The 1970s and 1980s saw significant advancements in SAR technology, driven by improvements in digital signal processing and the advent of more sophisticated computing capabilities. During this period, NASA launched the Seasat satellite in 1978, which carried the first spaceborne SAR. Seasat demonstrated the potential of SAR for various remote sensing applications, including oceanography, ice monitoring, and land usemapping.Following Seasat, numerous spaceborne SAR missions were launched, including the European Space Agency’s ERS-1 in 1991 and the Japanese JERS-1 in 1992. These missions expanded the use of SAR for environmental monitoring, disaster management, and geological studies. The development of interferometric SAR (InSAR) techniques in the 1990s furtherrevolutionized the field, enabling precise measurements of ground deformation and topographic mapping.In recent decades, SAR technology has continued to evolve with advancements in radarhardware, data processing algorithms, and the integration of SAR with other remote sensing technologies. Modern SAR systems, such as those on the Sentinel-1 and RADARSAT Constellation missions, offer high-resolution, multi-frequency imaging capabilities that support awide range of scientific, commercial, and humanitarian applications. [1]

### 2.2) Objectives of SAR development:

The primary objectives driving the development of SAR technology have been to achieve high-resolution imaging regardless of weather conditions and daylight, to enhance the ability to monitor and analyze dynamic environmental processes, and to support a variety of applications from military surveillance to civilian remote sensing. The ongoing advancements in SAR technology aim to provide ever-improving spatial and temporal resolution, enabling more detailed and timely insights into the Earth’s surface and atmospheric phenomena. [2]

### 2.3) Definition of Synthetic Aperture Radar:

Synthetic Aperture Radar (SAR) is a sophisticated remote sensing technique that uses radar signals transmitted from an antenna moving along a known path, typically aboard an aircraft or satellite. SAR generates high-resolution two-dimensional images of the Earth's surface by processing the reflected radar signals collected over multiple radar pulses. Unlike traditional radar systems that rely on the physical size of the antenna for resolution, SAR achieves fine resolution by synthesizinga virtual antenna aperture much larger than the physical antenna through the motion of the radar platform. This capability enables SAR to produce detailed images of terrain features, objects, and landscapes with consistent quality regardless of weather conditions or time of1 day, making it a valuable tool for various applications in environmental monitoring, disaster management, agriculture, defense, and scientific research. [3]

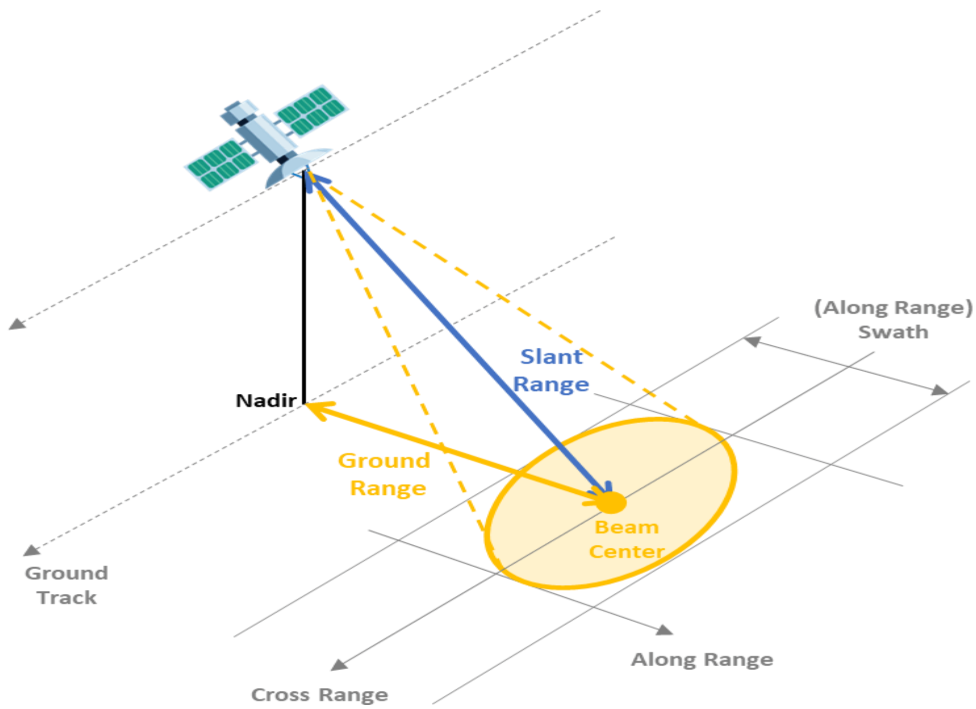



Figure 1.1: typical SAR imaging geometry.[60]

### 2.4) Types of products generated by SAR:

2.4.1) SLC (Single Look Complex): This format retains both amplitude and phase information, which is crucial for advanced applications like interferometry and polarimetric analysis. SLC images are complex numbers, allowing for detailed analysis of surface characteristics but require extensive preprocessing to be usable. [4]

2.4.2) GRD (Grond Range Detected): GRD images are processed to remove the phase information and are presented in real number format, focusing on detected amplitude. They are easier to use for applications such as land cover classification because they are already multi-looked and terrain-corrected, reducing speckle noise and making them more suitable for analysis without extensive preprocessing. [5]

### 2.4.3) Applications:

Both SLC and GRD images are utilized in various applications, including agriculture, forestry, and urban monitoring. GRD images are typically preferred for tasks requiring backscatter intensity, while SLC images are essential for applications needing phase information, such as interferometric studies. [6]

**Operation of Synthetic Aperture Radar (SAR):**

Synthetic Aperture Radar (SAR) works by emitting microwave signals towards the Earth's surface and recording the reflected signals. As the SAR device moves, it creates a large "synthetic aperture" by synthesizing the motion of the radar antenna, which results in a consistent spatial resolution over a range of viewing distances. This allows SAR to capture high-resolution images of the Earth's surface, even at night or during inclement weather. The process involves complex information processing to create two-dimensional images with fine azimuth and range resolution. SAR images are used in various applications, including environmental monitoring, earth-resource mapping, and military systems. The interpretation of SAR images requires an understanding of the non-intuitive, side-looking geometry and the characteristics of radar signals. SAR is a valuable technology due to its ability to provide high-resolution images in a 24-hours, all-weather manner, making it suitable for a wide range of applications

The Synthetic Aperture Radar (SAR) operates based on advanced principles of radar signal processing and imaging from moving platforms such as satellites or aircraft.

### 2.5.1) Radar Signal Generation :

**Signal Emission:** SAR emits radar pulses towards the Earth's surface from an antenna mounted on a moving platform, such as a satellite orbiting the Earth. [7]

**Signal Reflection:** These radar pulses are reflected back from objects and structures on the Earth's surface. The reflection varies depending on the properties of materials and the terrain features encountered. [8]

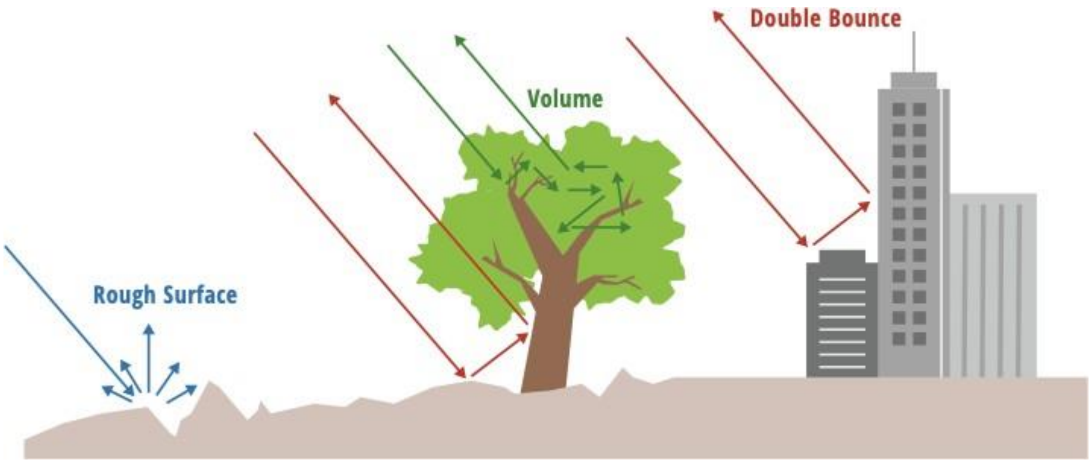



Figure 1.2: signal emission and reflection.[61]

### 2.5.2) Data Acquisition:

- Data Collection: The SAR antenna receives the radar signals reflected from the Earth's surface as the platform moves along its predefined path.
- Sampling: The received signals are sampled at regular intervals to capture spatial and temporal information necessary for image reconstruction.
- Signal Processing: The raw radar data collected is processed either onboard the platform or on the ground. This processing includes correction for atmospheric effects, instrumental errors, and compensation for platform motion.

Image Formation: By exploiting the relative motion between the platform and the Earth's surface(or synthesizing a virtual aperture), SAR reconstructs a high-resolution image of the observed area.This image combines data from multiple positions along the platform's trajectory, achieving spatial resolution much finer than possible with a physical radar antenna of equivalent size. [9]

## 2.6) Polarization:

Polarization in Synthetic Aperture Radar (SAR) refers to the orientation of the electric field of the transmitted radar waves and the received radar echoes. SAR systems can transmit and receiveradar signals in different polarization states, which affects the characteristics of the returned signal and provides valuable information about the properties of the observed target or surface. [10]

### 2.6.1) Types of Polarization in SAR:

Single Polarization (HH or VV):

HH (Horizontal Transmit, Horizontal Receive): In HH polarization, the radar transmits waves with horizontal polarization and receives echoes with horizontal polarization. This polarization is sensitive to surface roughness and is commonly used in terrain mapping and urban area analysis.

VV (Vertical Transmit, Vertical Receive): VV polarization involves transmitting and receiving radar waves with vertical polarization. It is sensitive to vegetation structure and moisture content, making it useful for applications such as agriculture monitoring and forest mapping.

Dual Polarization (HH/VV or HV):

HH/VV: This configuration involves transmitting in both horizontal and vertical polarizations and receiving echoes in both polarizations. Dual polarization enhances the discrimination between different types of targets and improves the classification accuracy of SAR imagery. It is beneficialfor applications requiring detailed characterization of surface properties and target classification. HV (Horizontal Transmit, Vertical Receive): HV polarization transmits waves with horizontal polarization and receives echoes with vertical polarization. This polarization combination is usefulfor detecting man-made structures and distinguishing between different types of surfaces. [11]

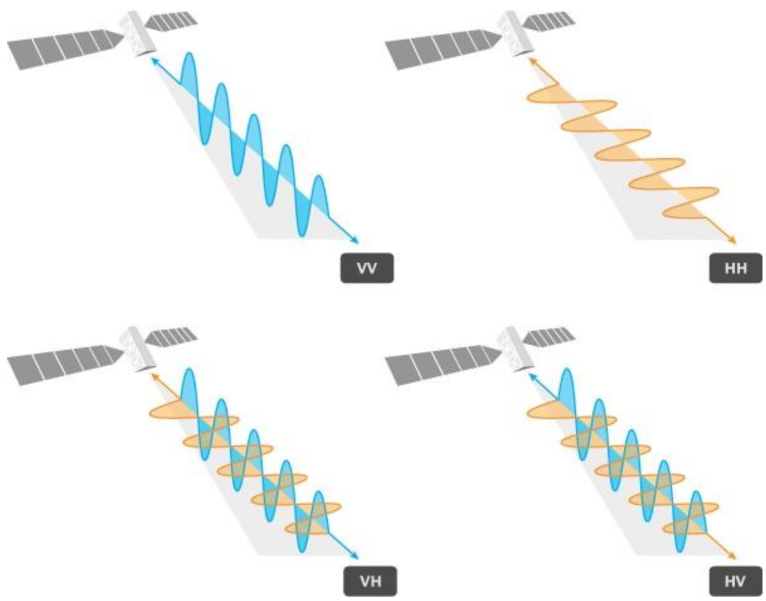



Figure 1.3: different polarizations.[62]

### 2.6.2) Selection of Polarization mode:

The choice of polarization mode in SAR depends on the specific application requirements, the characteristics of the target or surface of interest, and environmental conditions. Understanding polarization characteristics and their implications enables SAR systems to effectively capture and analyze diverse aspects of the Earth's surface and targets with high precision and accuracy. [12]

## 2.7) Acquisition modes:

Acquisition modes refer to different operational configurations and parameters used to collect radar data. These modes are tailored to specific imaging requirements, such as spatial resolution, coverage area, and imaging geometry. Most of the common used acquisition modes in SAR are the followings:

### 2.7.1) Stripmap Mode:

In stripmap mode, the radar antenna points straight down (nadir) during data acquisition while the platform (satellite or aircraft) moves along its path.

Characteristics: Provides high-resolution images with uniform resolution across the entire swath. Suitable for detailed mapping and monitoring of urban areas, infrastructure, and terrain features. Typically offers moderate swath widths and higher spatial resolution compared to other modes. [13]

### 2.7.2) ScanSAR Mode:

ScanSAR (Scan Synthetic Aperture Radar) mode employs a wider antenna beam that scans acrossa larger area rather than focusing on a single straight path.

Characteristics: Covers a wide swath width, making it suitable for broad-area surveillance and monitoring applications. Sacrifices spatial resolution compared to stripmap mode due to the wider beam and complex data processing. Can be implemented in various sub-modes (e.g., Wide-Swath, Global Monitoring) to optimize coverage and resolution trade-offs. [14]

### 2.7.3) Spotlight Mode:

Spotlight mode narrows the antenna beam significantly to focus on a smaller area on the ground.Characteristics: Provides very high spatial resolution imagery by concentrating radar pulses on a smaller ground area. Requires precise pointing and positioning of the radar antenna during data acquisition. Suitable for detailed mapping of specific targets or areas requiring high-resolution imaging, such as urban centers or critical infrastructure. [15]

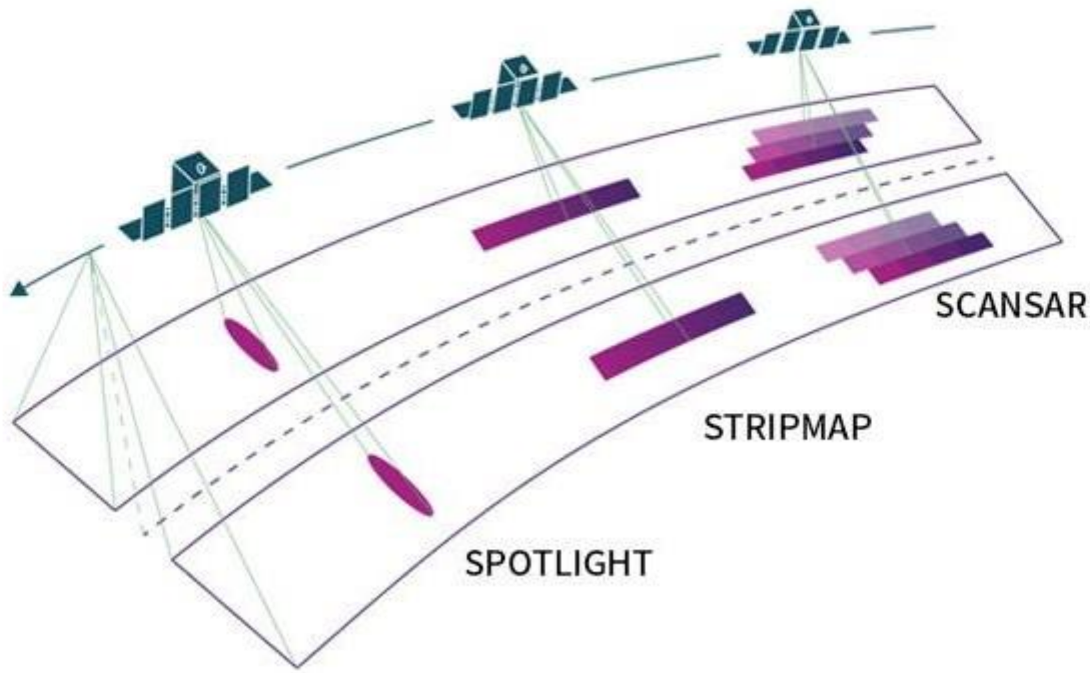



Figure 1.4: acquisition modes.[63]

### 2.7.4) Selection of Acquisition Mode:

The selection of SAR acquisition mode depends on the specific objectives of the imaging task, including spatial resolution requirements, coverage area, target characteristics, and environmental conditions. Each mode offers distinct advantages and trade-offs in terms of resolution, swath width, imaging geometry, and data processing complexity, allowing SAR systems to effectively meet diverse application needs in remote sensing, environmental monitoring, disaster management, and scientific research. [16]

## 2.8) Frequency Bands and Wavelengths:

Synthetic Aperture Radar (SAR) operates in different frequency bands within the microwave portion of the electromagnetic spectrum. The choice of frequency band influences SAR's performance characteristics and its suitability for various applications. Most of the used wavelengths and bands commonly used in SAR are:

### 2.8.1) L-band (1-2 GHz):

Wavelength: Approximately 15-30 cm.

Characteristics: L-band SAR is known for its ability to penetrate vegetation and soil, making it suitable for applications requiring vegetation monitoring, soil moisture estimation, and subsurface imaging. It provides moderate resolution and good penetration capabilities.

### 2.8.2) S-band (2-4 GHz):

Wavelength: Approximately 7.5-15 cm.

Characteristics: S-band SAR offers higher resolution than L-band and good penetration capabilities through vegetation. It is used in applications such as agriculture monitoring, urban planning, and land cover classification.

### 2.8.3) C-band (4-8 GHz):

Wavelength: Approximately 3.75-7.5 cm.

Characteristics: C-band SAR provides a balance between resolution, penetration capability, and sensitivity to surface roughness. It is widely used for environmental monitoring, disaster management, and maritime surveillance due to its all-weather imaging capability.

### 2.8.4) X-band (8-12 GHz):

Wavelength: Approximately 2.5-3.75 cm.

Characteristics: X-band SAR offers high spatial resolution and is sensitive to small-scale surface features. It is suitable for applications requiring fine detail, such as urban monitoring, infrastructure assessment, and defense applications.

### 2.8.5) Ku-band (12-18 GHz):

Wavelength: Approximately 1.67-2.5 cm.

Characteristics: Ku-band SAR provides very high spatial resolution and is particularly sensitive to surface roughness variations. It is used for applications demanding detailed surface analysis, suchas precision agriculture, forestry, and coastal zone monitoring.

2.8.6) Ka-band (26.5-40 GHz): Wavelength: Approximately 0.75-1.1 cm.

Characteristics: Ka-band SAR offers extremely high spatial resolution and sensitivity to small-scale surface features. It is used in specialized applications requiring ultra-high resolution, such as archaeological studies, industrial monitoring, and urban planning. [17]

## 2.9) Utility of Synthetic Aperture Radar (SAR):

Synthetic Aperture Radar (SAR) finds diverse applications across several fields due to its unique capabilities in remote sensing and imaging.

Earth Observation and Environmental Monitoring**:**

SAR is extensively used in Earth observation for monitoring various environmental parameters:

- Land Use and Land Cover Mapping: SAR images provide detailed information on vegetation cover,urban areas, and agricultural activities.
- Deforestation and Forest Monitoring: SAR can penetrate cloud cover and monitor changes in forestcover over time.

Agriculture

- Flood Mapping: SAR can detect flooded areas by distinguishing between water and land surfacesbased on their backscatter characteristics.
- Glacier Monitoring: SAR helps in monitoring glacier dynamics and changes in ice sheets.
- Crop Monitoring: SAR aids in monitoring crop growth stages, identifying crop types, and assessing crop health by detecting moisture content in soil and vegetation.
- Soil Moisture Estimation: SAR sensors measure backscatter from soil surfaces, providing data for estimating soil moisture content, which is crucial for irrigation management and drought monitoring

Urban Planning and Infrastructure Monitoring:

- Urban Growth and Planning: SAR images assist in urban planning by providing information on urban expansion, infrastructure development, and land use changes.
- Infrastructure Monitoring: SAR detects ground subsidence, infrastructure stability, and deformation of structures like bridges.

Disaster Management:

- Emergency Response: SAR provides rapid and accurate mapping of disaster-affected areas, facilitating search and rescue operations.
- Damage Assessment: SAR images help in assessing damage to infrastructure and human settlements caused by natural disasters such as earthquakes, hurricanes, and tsunamis.

Marine and Coastal Applications:

- Ship Detection: SAR can detect and monitor maritime traffic, aiding in maritime surveillance andillegal fishing detection.
- Oceanography: SAR measures ocean surface features such as waves, currents, and wind patterns,providing valuable data for oceanographic research.

Defense and Security:

- Surveillance: SAR is used for reconnaissance, surveillance, and intelligence gathering due to its all-weather capability and ability to operate at night.
- Border Monitoring: SAR assists in monitoring borders and detecting illegal crossings and activitiesin remote areas.

Scientific Research:

- Geological Mapping: SAR images provide insights into geological structures, fault lines, and mineral exploration.
- Environmental Studies: SAR data supports ecological studies, biodiversity monitoring, and habitatmapping in remote and inaccessible regions.

Aviation and Navigation:

- Terrain Mapping: SAR aids in creating high-resolution digital elevation models (DEMs) for aviation safety and navigation purposes. [18]

## 2.10) Spaceborne and airborne:

2.10.1) Spaceborne Synthetic Aperture Radar (SAR): Spaceborne SAR refers to radar systeme mounted on satellites orbiting Earth. These systems operate from space, typically at altitudes ranging from a few hundred kilometers to several hundred kilometers above the Earth's surface. Spaceborne SAR sensors capture microwave signals emitted towards the Earth's surface and measure the

Backscattered signals to generate high-resolution images of the planet's surface. They are used for various applications such as environmental monitoring, disaster management, agriculture, and military surveillance. [19]

2.10.2) Airborne Synthetic Aperture Radar (SAR): Airborne SAR refers to radar systems mounted on aircraft. These systems operate from airborne platforms, including airplanes and helicopters, flying at lower altitudes compared to spaceborne SAR satellites. Airborne SAR sensors emit microwave signals towards the Earth's surface and measure the backscattered signals to generate high-resolution images. Airborne SAR is particularly useful for applications requiring flexibility in imaging locations, higher spatial resolution, or rapid deployment capabilities. It is commonly usedin mapping, surveillance, and environmental monitoring tasks. [20]

### 2.10.3) Advantages of Spaceborne SAR:

- Global Coverage: Spaceborne SAR satellites can provide global coverage of the Earth's surface, including remote and inaccessible regions, making them ideal for large-scale mapping andmonitoring.
- Repetitive Coverage: Satellites in orbit can revisit the same area periodically, allowing for regular monitoring and tracking of changes over time. This is crucial for environmental monitoring, disaster management, and agriculture.
- Consistent Imaging Geometry: Spaceborne SAR maintains a consistent imaging geometry due to its fixed orbit and sensor characteristics, which simplifies data processing and comparison betweendifferent acquisitions.
- Global Collaboration: Data from spaceborne SAR satellites are often shared internationally, facilitating global collaboration in research, disaster response, and environmental monitoring efforts. [21]

### 2.10.4) Advantages of Airborne SAR:

- High Spatial Resolution: Airborne SAR systems can achieve higher spatial resolution compared to spaceborne SAR, especially when flying at lower altitudes. This makes them suitable for detailed mapping and monitoring of smaller areas.
- Flexibility in Target Selection: Aircraft can be maneuvered to target specific areas of interest quickly, allowing for on-demand data collection and response to dynamic events such as natural disasters or emergencies.
- Customizable Sensor Payloads: Airborne SAR platforms can accommodate various sensor configurations and additional instruments, enabling multi-sensor integration and customized payloads for specific mission objectives.
- Validation and Calibration: Airborne SAR missions can serve as validation and calibration platforms for spaceborne SAR sensors, ensuring accuracy and consistency in remote sensing data.
- Operational Control: Operators have direct control over flight paths and imaging parameters, allowing for real-time adjustments and optimization of data collection based on changing conditions or requirements. [22]

## 3/Speckle phenomena in SAR images:

### 3.1) introduction to speckle :

One of the persistent challenges in SAR imaging is the presence of speckle noise, which manifests as grainy or granular interference patterns in images. Speckle arises due to the coherent nature of radar waves interacting with rough surfaces or distributed scatters within the target scene. Understanding and mitigating speckle noise is crucial for enhancing the interpretability and quantitative analysis of SAR data. In SAR images, “speckle” refers to the grainy or granular appearance caused by coherent interference of electromagnetic waves scattered by different targets within each resolution cell of the radar. This phenomenon is intrinsic to SAR imaging and arises due to the random nature of the scattering process from various surface features. Speckle occurs because SAR images are formed by coherent waves that interfere constructively or destructively when they interact with different scatterers (such as terrain features, vegetation, buildings, etc.) within the resolution cell. This results in a speckled appearance rather than a smooth intensity distribution. Speckle is a statistical phenomenon. The intensity of a pixel in a SAR image is not only influenced by the reflectivity of the underlying surface but also by the phase relationships between the scattered waves. This randomness leads to the speckled pattern. It can obscure fine details in SAR images and make visual interpretation challenging. It can affect the detection of small objects or subtle changes in the scene. Thus, speckle reduction techniques are often employed to improve the interpretability of SAR images. [23]

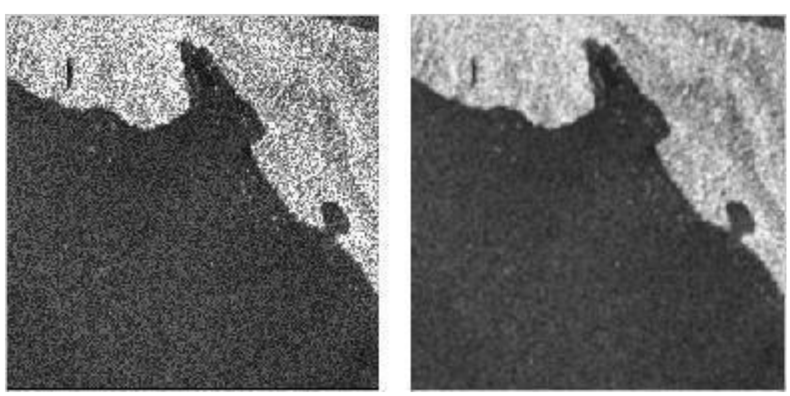


Figure 1.5: image with speckle .[64]

**3.2) Speckle Reduction:** Various techniques exist to mitigate speckle effects, such as multi-looking (averaging multiple adjacent pixels), filtering (using mathematical filters to smooth the image), and speckle modeling (statistically modeling and removing speckle while preserving important image features).

Reducing speckle in SAR images is important for improving image quality and enhancing the interpretability of the data. [24]

### 3.3) Methods used in Speckle filtering:

#### 3.3.1) Multi-looking (Spatial Averaging):

Multi-looking involves averaging multiple adjacent pixels (looks) within a defined window. This process effectively reduces the noise level, including speckle, at the expense of spatial resolution. The degree of speckle reduction depends on the number of looks used. [25]

#### 3.3.2) Filters:

- Lee Filter: The Lee filter is a spatial domain filter that replaces each pixel with a weighted average of neighboring pixels, taking into account both the local mean and variance. It effectively suppresses speckle while preserving image features.
- Frost Filter: The Frost filter is another spatial domain filter that estimates the true signal by considering statistical properties of speckle. It can preserve edges and fine details better than simpler averaging techniques.
- Gamma Map Filter: This filter is based on the statistical properties of the image and applies a non-linear transformation to suppress speckle. [26]

#### 3.3.3) Wavelet Transform:

Wavelet-based methods decompose the image into different frequency bands using wavelet transforms and then apply filtering to suppress speckle at different scales. Wavelet techniques can preserve edges and fine details better than traditional filters.

The choice of speckle reduction technique depends on factors such as the specific characteristicsof the SAR image (resolution, noise level), the desired level of speckle reduction, and the computational resources available. Each technique has its advantages and limitations, and the optimal approach may vary depending on the application and specific requirements. [27]

## 4) Conclusion:

In this chapter, we explored Synthetic Aperture Radar (SAR) imaging, a powerful remote sensing technology offering high-resolution observations of Earth's surface under all weather conditions.

Despite its advantages, SAR images exhibit speckle, a granular noise pattern that complicates visual interpretation and analysis. Understanding the origins and characteristics of speckle is crucial for implementing effective mitigation strategies.

# Chapter 2: overview about Deep Learning.

## 1) Introduction:

In this chapter, we will delve into an introduction to Artificial Intelligence (AI) and its transformative applications in despeckling Synthetic Aperture Radar (SAR) images. SAR technology, renowned for its ability to provide high-resolution and all-weather imaging of Earth's surface, is often hindered by speckle noise—a granular interference pattern that complicates image interpretation and analysis. Traditional methods for speckle reduction have limitations in preserving image details and texture, prompting the exploration of AI-driven approaches. This chapter aims to explore how AI, encompassing machine learning and deep learning techniques, can effectively mitigate speckle noise in SAR imagery, thereby enhancing data quality and facilitating more accurate information extraction for critical applications in geosciences, environmental monitoring, and beyond.

Before understanding what Deep Learning is, we need to introduce two main concepts: The firstis the concept of Artificial Intelligence. The second is Machine Learning (Automatic Learning).

### 1.1) Artificial Intelligence:

Artificial Intelligence (AI) represents a transformative force reshaping industries, societies, and our understanding of intelligent behavior. At its core, AI encompasses the development of computer systems capable of performing tasks that typically require human intelligence. These Tasks range from understanding natural language and recognizing patterns in data to making decisions based on complex reasoning. The field of AI has evolved significantly since its inception, driven by advances in computing power, algorithms, and access to vast amounts of data. Key to its progress are machine learning (ML) and deep learning (DL), subfields that empower machinesto learn from experience, adapt to new inputs, and perform tasks autonomously.

AI finds applications across diverse domains, revolutionizing industries such as healthcare, finance, transportation, and beyond. In healthcare, AI aids in medical diagnosis, personalized treatment plans, and drug discovery. Financial institutions use AI for fraud detection, algorithmic trading, and customer service automation. Autonomous vehicles rely on AI for navigation and decision- making, enhancing safety and efficiency. [28]

### 1.2) Machine Learning:

Machine Learning (ML) is a subfield of Artificial Intelligence (AI) that focuses on enabling machines to learn from data and improve their performance over time without being explicitly programmed. It encompasses a set of algorithms and techniques that allow computers to discover patterns, make decisions, and solve problems based on empirical data.

At the core of ML lies the concept of learning from data. Instead of following explicit instructions, ML algorithms iteratively learn from examples and adjust their models to capture underlying patterns in the data. This process involves:

- Training Data: A set of labeled or unlabeled examples used to train the ML model. Labeled data includes input-output pairs used in supervised learning, while unsupervised learning uses unlabeled data to find patterns and structures.
- Feature Extraction: Identifying and selecting relevant features or attributes from the data that are essential for the learning process.
- Model Training: Using the training data to optimize the model parameters or structure, enabling itto make accurate predictions or decisions on new, unseen data.
- Evaluation: Assessing the performance of the trained model using metrics such as accuracy, precision, recall, or specific domain-dependent measures. [29]

### 1.2.1) Types of Machine Learning ML:

This can be broadly categorized into several types:

- Supervised Learning: Involves training models on labeled data to make predictions or classify new data into predefined categories. Examples include regression (predicting continuous outputs) andclassification tasks.
- Unsupervised Learning: Involves finding hidden patterns or structures in unlabeled data, such as clustering similar data points together or dimensionality reduction techniques.
- Reinforcement Learning: Focuses on training agents to make sequential decisions through interaction with an environment, receiving rewards or penalties based on their actions. [30]

## 2) Deep Learning:

**2.1) Deep Learning (DL)** is a subset of Machine Learning (ML) that focuses on learning representations of data through neural networks with multiple layers. This approach has gained significant attention due to its ability to handle and learn from large amounts of complex data, producing highly accurate predictions and classification. [31]

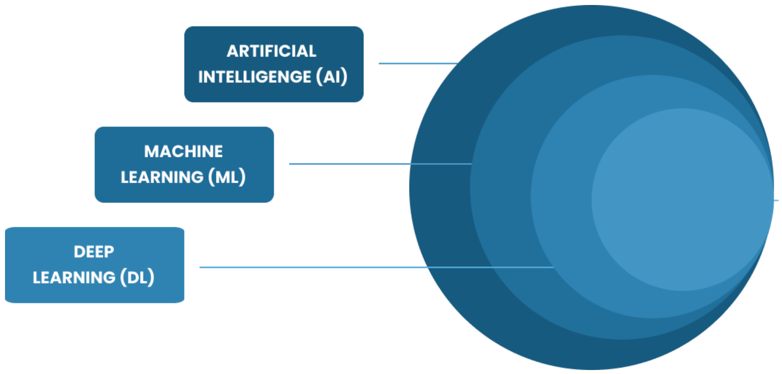



Figure 2.1: : difference between AI ,ML ,DL.[65]

**2.2) Artificial neutral network:** An Artificial Neural Network (ANN) is a computational model inspired by the structure and function of biological neural networks. ANNs consist of interconnected nodes called artificial neurons or units organized into layers: an input layer, one or more hidden layers, and an output layer. Each connection between neurons is associated with a weight that adjusts during the learning process to optimize the network's performance. [32]

## 2.3) Key concept of neural networks

2.3.1) Neuron Structure: In an artificial neuron, inputs are received with associated weights, summed upin the neuron's activation function, and passed through an activation function to produce an output. [33]

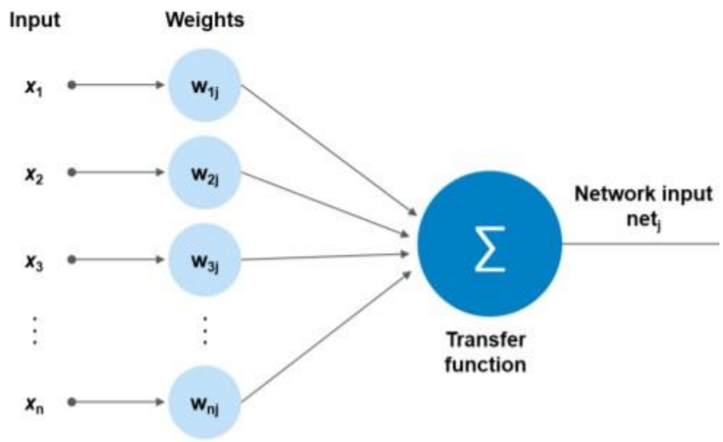



Figure 2.2: artificial neuron structure.[66]

2.3.2) Activation Function: Determines the output of a neuron given its weighted inputs, often introducing non-linearity crucial for learning complex patterns.

- The ReLU activation function is defined as:

$$\boxed{\text{ReLU}(x) = \max(0, x) \text{ ..........................} (2.1)}$$

Where x is the input to the activation function.

Characteristics of ReLU:

Output Range: The output is in the range [0, ∞). For any input less than 0, the output is 0. For any input greater than or equal to 0, the output is equal to the input.

- The Sigmoid activation function is defined as:

$$\boxed{\text{Sigmoid}(x) = \frac{1}{1+e^{-x}} \text{ .................} (2.2)}$$

Where e is the base of the natural logarithm, and xxx is the input to the activation function.

Characteristics of Sigmoid:

Output Range: The output is in the range (0, 1 ) (0, 1) (0,1). It maps the input values to a value between 0 And 1, making it suitable for probabilistic interpretations. [34]

2.3.3) Layers: Neurons are organized into layers within a neural network. The input layer receives raw data, hidden layers process intermediate representations, and the output layer produces the final output. [35]

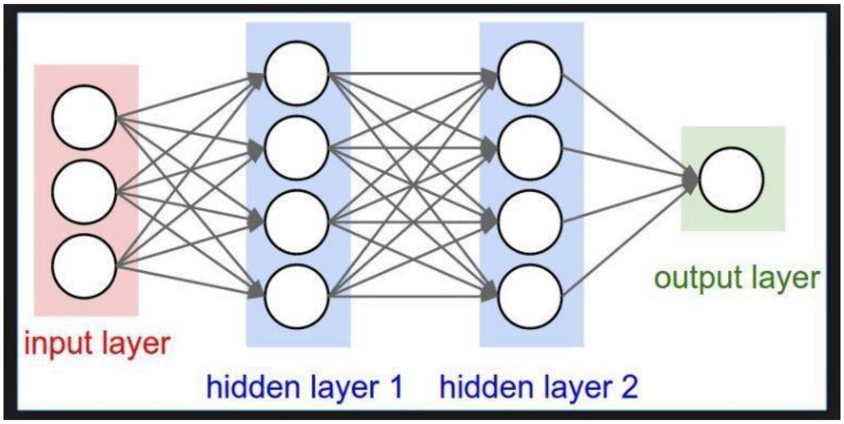



Figure 2.3: different layers in neural networks.[67]

## 2.4) Techniques of artificial neutral networks:

2.4.1) Deep Neural Networks (DNNs): These networks contain multiple hidden layers between the input and output layers, allowing them to learn intricate patterns and representations from raw data.

Each layer extracts features at increasing levels of abstraction, which is essential for complex data analysis.

2.4.2) Convolutional Neural Networks (CNNs): CNNs are specialized DNN architectures designed for processing grid-like data, such as images and videos. They use convolutional layers to automatically learn spatial hierarchies of features, making them particularly effective for image and video analysis. [36]

## 2.5) CNNs methods for Despeckling SAR Images:

Convolutional Neural Networks (CNNs) are a class of deep learning models particularly well-suited for image processing tasks. They have been successfully applied to despeckling SAR images due to their ability to capture spatial hierarchies of features and patterns in noisy data.

### 2.5.1) Basic CNN Architecture:

- Convolutional Layers: These layers apply convolution operations to the input image usinga set of learnable filters or kernels. Each filter captures specific features such as edges, textures, and patterns. The output of a convolutional layer is a set of feature maps that highlight different aspects of the input image.

- Activation Functions:

 Non-linear activation functions, such as ReLU (Rectified Linear Unit), are applied to the featuremaps to introduce non-linearity and enable the network to learn complex patterns.

- Filter (Kernel): A small matrix is used to detect features in the input.
- Stride: The number of pixels by which the filter matrix is moved across the inputmatrix.
- Padding: Adding extra pixels around the input matrix to control the spatial sizeof the output.
- Pooling Layers:

Pooling layers, such as max pooling or average pooling, reduce the spatial dimensions of the feature maps, providing spatial invariance and reducing the computational load. This helps in capturing the most significant features while discarding redundant information.

- Fully Connected Layers:

These layers connect every neuron in one layer to every neuron in the next layer, enabling high- level reasoning based on the features extracted by the convolutional layers. [37]

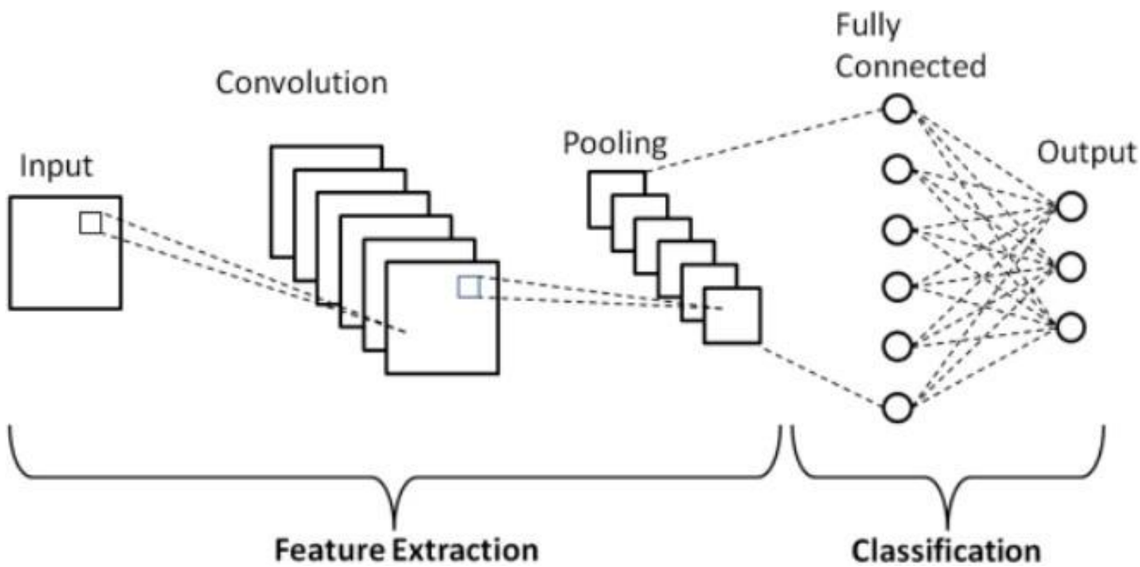



Figure 2.4: CNN architecture.[68]

### 2.6) CNNs advantages:

CNNs offer superior noise reduction for SAR images by effectively suppressing speckle noise while preserving essential details, thanks to their adaptive filters and multi-scale feature capture. They automatically extract relevant features, eliminating the need for manual feature engineering. Their robustness allows them to generalize well across different datasets and noise levels, and pre-trained models can be fine-tuned for SAR de-speckling. CNNs maintain spatial relationships and exhibit invariance to transformations like translation and rotation. Their scalable architectures and ability to integrate with other methods enhance performance, and they provide efficient real-time processing. Overall, CNNs are powerful, flexible, and efficient tools for improving SAR image quality. [38]

## 3/ Classification and Prediction in ML:

**3.1) Classification**: Classification is a type of supervised learning where the goal is to assign data points to predefined categories or classes. Essentially, the model learns to categorize input data into one of several classes based on training data. [39]

### 3.2) Concepts of classification:

- Training Data: You provide a dataset where the classes are known. For example, if you're classifying emails as spam or not spam, the training data would include emails labeled as "spam" or "not spam."
- Feature Extraction: The model uses features from the data (e.g., words in the email, frequency of certain terms) to learn patterns associated with each class.
- Model Training: Algorithms like decision trees, logistic regression, support vector machines, or neural networks are trained to recognize these patterns.
- Prediction: When given new, unlabeled data, the model predicts the class based on what it has learned. [40]

### 3.3) Prediction :

Prediction in machine learning involves using a trained model to make forecasts or estimates about unknown or future data points. It can be applied to both regression (predicting continuous values) and classification (predicting categorical values) tasks. [41]

### 3.4) Concepts of prediction:

- Regression vs. Classification: Regression involves predicting a continuous output (exhouse prices), while classification involves predicting discrete labels (ex spam or not spam).
- Feature Selection: Choosing the relevant features that will be used by the model to make predictions.
- Model Training and Testing: The model is trained on historical data and then tested on newdata to evaluate its predictive accuracy. [42]

## 4)Differences between Classification and Prediction in Machine Learning:

Classification and prediction are both essential tasks in machine learning, each serving distinct purposes. Classification involves assigning categorical labels to input data, such as determining whether an email is “spam” or “not spam,” using algorithms like logistic regression, SVM, and decision trees. It outputs discrete categories and evaluates performance using metrics like accuracy, precision, and confusion matrices. Prediction, on the other hand, focuses on estimating continuous values or forecasting future outcomes, such as predicting house prices or stock market trends, using algorithms like linear regression and ARIMA. It outputs continuous values and evaluates performance using metrics like mean squared error (MSE) and R-squared. While classification deals with categorizing data into predefined classes, prediction aims to estimate unknown values based on patterns learned from historical data. Understanding these differences is crucial for selecting the right approach and algorithms for specific machine learning problems. [43]

## 5/CNNs Architectures:

These architectures represent the evolution of techniques aimed at improving SAR image quality:

### 5.1) U-Net Architecture:

U-Net is a convolutional neural network (CNN) architecture that has gained popularity for its effectiveness in biomedical image segmentation tasks. Developed by Ronneberger et al., UNet is characterized by a symmetric encoder-decoder structure. The encoder path captures context through successive convolutional and pooling layers, while the decoder path uses upsampling and concatenation operations to recover spatial information lost during pooling. This architecture is particularly suited for tasks requiring precise localization of features, such as identifying boundaries and structures in medical images. Beyond biomedical applications, UNet has found

Versatile use in image processing domains like SAR (Synthetic Aperture Radar) image despeckling, where it aids in accurately delineating structures while enhancing image quality.[44]

### 5.2) SAR2SAR:

SAR2SAR refers to methodologies and algorithms specifically designed for enhancing SAR imagery through various processing techniques. In SAR applications, these methods typically involve transformations or enhancements aimed at improving image quality, such as reducing speckle noise, enhancing resolution, or extracting meaningful features. SAR2SAR techniques are crucial for maximizing the utility of SAR data in fields like environmental monitoring, disaster management, and agricultural analysis, where high-quality, noise-free images are essential for accurate interpretation and decision-making. [45]

### 5.3) Speckle2Void:

Speckle2Void is an innovative approach to SAR image despeckling that leverages deep learning, specifically Generative Adversarial Networks (GANs). Developed to address the challenges posed by speckle noise, Speckle2Void operates by training a generator network to predict clean SAR images from their speckled counterparts. This method harnesses the power of adversarial training, where a discriminator network guides the generator to produce images that are indistinguishable from real clean images. By capturing complex spatial dependencies and patterns in SAR data, Speckle2Void offers a promising solution to enhance image quality and facilitate more accurate analysis in SAR applications. [46]

**5.4)BM3D (Block Matching 3D):** BM3D is a renowned algorithm for image denoising, includingSAR image despeckling, based on non-local means (NLM) principles. This method partitions theimage into overlapping blocks, then performs collaborative filtering to reduce noise within similarblocks. BM3D exploits the redundancy and spatial correlations present in natural images to effectively suppress speckle noise while preserving important image features. Widely recognizedfor its robust performance, BM3D has become a cornerstone in SAR image processing, providingreliable noise reduction capabilities that contribute to clearer and more interpretable SAR imageryfor diverse applications. [47]

### 5.4.1) the history of BM3D:

The BM3D (Block Matching 3D) algorithm was first introduced in 2007 by Kostadin Dabov, Alessandro Foi, Vladimir Katkovnik, and Karen Egiazarian
in their paper titled "Image Denoising by Sparse 3D Transform-Domain Collaborative Filtering." It was developed as an improvement over earlier denoising methods, particularly addressing the limitations of traditional filters, such as Gaussian or median filtering, which struggled to effectively remove noise without blurring image details.

BM3D was born from the idea of utilizing both local and non-local similarities within images to achieve superior denoising. The algorithm builds on the principles of patch-based methods and non-local means (NLM), which groups similar patches from across the image. By extending this approach to the 3D transform domain, BM3D set a new standard in image denoising, offering a significant advancement in terms of both noise reduction and preservation of image structures like edges and textures.

Since its introduction, BM3D has become one of the most widely used and benchmarked algorithms in the field of image processing, particularly in areas like medical imaging, digital photography, and remote sensing (such as SAR). Its success has also inspired further developments and variants to address specific noise types and image restoration tasks. [48]

### 5.4.2) BM3D Advantages:

The BM3D algorithm offers several key advantages in image denoising. It effectively reduces noise while preserving important details like edges and textures, making it ideal for complex images such as SAR or medical images. By leveraging both local and non-local similarities through block grouping and collaborative filtering, BM3D achieves high-quality denoising results. It excels in handling various noise types and complex environments, and its flexibility allows for easy adaptation to different tasks.

Additionally, BM3D's structure supports parallel processing, enhancing its efficiency for large-scale image processing. [49]

## 6/Conclusion:

In conclusion, the second chapter of this thesis provided a detailed overview of key concepts in Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning. It differentiated between classification, which assigns labels to data, and prediction, which forecasts outcomes based on past data. The chapter also explored Convolutional Neural Networks (CNNs), highlighting their crucial role in image processing tasks like classification.

A significant focus was placed on the BM3D algorithm, its architecture, history, and advantages. Its two-stage denoising process and ability to preserve fine details make it highly effective, particularly in applications like SAR image despeckling.

# Chapter 3: Implementation and Results

## 1/Introduction :

After having in the previous chapter an introduction to artificial intelligence as well as machine Learning, and outlining the basic knowledge of deep learning, providing also an overview of its various applications, neural networks, and the explanation of the functioning principle of these networks.

In this chapter, we will review the materials used in our research. We will utilize the Bm3d technique code.

For this, we will work with the Python programming language and libraries such as TensorFlow and Keras for learning and classification purposes.

## 2/ Presentation of Tools

### 2.1) Hardware:

The general hardware information used in our implementation is:

HP Laptop where its properties are:

- Windows 10 Enterprise.
- AMD Turion™ II Dual-Core Mobile M500 2.20 GHz.
- 4GB RAM.
- 64-bit Operating System, x64 Processor.

Lenovo Laptop where its properties are:

- Windows 10 Enterprise.
- Intel® Core ™ i3-5010U CPU@ 2.10 GHz.
- 4GB RAM.
- 64-bit Operating System, x64 Processor.

### 2.2) Software:

- VS Code (Visual Studio Code): is a free code editor developed by Microsoft. It offers support for a variety of programming languages and has features such as syntax highlighting, code completion, debugging features, and native Git integration. VS Code is highly customizable through extensions, allowing users to customize the editor to suit their specific needs and preferences.
  Known for its light weight, speed, and cross-platform compatibility, it is popular among developers for a variety of software development projects.

It is a lightweight yet powerful source code editor, available for Windows, MacOS, and Linux. It comes with built-in support for JavaScript, Typescript, and Node.js and has a rich ecosystem of extensions for other languages and runtime environments (such as C++, C#, Java, Python, PHP, Go, .NET). [50]

Figure 3.1 : vs code logo[69]

- PYTHON:

  Python is a programming language, one of the high-level languages, characterized by simple writing and reading, easy to learn, using an open programming style, and scalable. Python is a versatile language used in many fields, such as creating standalone programs using familiar graphical interfaces and running web programs, and its use as a scripting language to control the performance of the most popular programs. In general, Python can be used to program simple programs for beginners and to undertake large projects simultaneously with any other programming language. It is often recommended for programming beginners to learn this language as it is one of the fastest-learning software languages. En ligne Available: https://www.python.org/. [51]

Figure 3.2: python logo[70]

- Keras:

Keras is an open-source Deep Learning framework for Python, capable of running on TensorFlow. It is written by Francis Chollet, a member of the Google team. Keras is used in a large number of startups, research laboratories (including CERN, Microsoft Research, and NASA), and major companies such as Netflix, Yelp, Square, Uber, Google, etc. It was developed as part of the research effort of the ONEIROS project (Open-ended Neuro Electronic Intelligent Robot Operating System).

In 2017, the Google TensorFlow team decided to provide support for Keras and integrate it into the main TensorFlow library.

It provides a set of higher-level and more intuitive abstractions that make configuring neural networks easier. (Keras.io, En ligne. Available: [http://KERAS.io](http://KERAS.io)) [52]

Figure 3.3: Keras Logo.[71]

- TensorFlow:

TensorFlow is a programming framework for numerical computation created by Google and became an open-source framework in November 2015. Its flexible architecture allows for easy deployment of computation on various platforms (CPU, GPU, TPU). Since then, TensorFlow has continued to gain significant importance and popularity and quickly become one of the most widely used frameworks for Deep Learning. Its name is inspired by the fact that the current operations of neural networks are primarily performed via a multidimensional data array, called Tensors, which is the equivalent of a matrix. ( https ://www.tensorflow.org/.) [53]

Figure 3.4: Tensorflow logo[72]

- Anaconda

Anaconda is a free and open-source distribution of the Python and R programming languages applied to the development of applications dedicated to data science and Deep Learning (large-scale data processing, predictive analysis, scientific computing). It aims to simplify package management and deployment. Package versions are managed by the conda package management system. The Anaconda distribution is used by over 6 million users and includes more than 250 popular data science packages tailored for Windows, Linux, and MacOS https ://www.anaconda.com/distribution/.[54]

Figure 3.5: Anaconda logo[73]

- Numpy:

Numpy is a basic scientific computing package for Python. It offers a multidimensional array object, various derived objects (such as masked arrays and matrices), and a set of fast array operations such as mathematics, logic, pattern manipulation, sorting, selection, etc. This Python library includes routines for discrete Fourier transforms, basic linear algebra, basic statistical operations, random simulations, etc. [Andersen, 2022]. [55]

Figure 3.6: Numpy logo[74]

- Matplotlib:

Matplotlib is a complete library for creating static, animated and interactive visualizations in Python. [56]

## 3) Experimental data and quality evaluation metrics:

### 3.1) Database:

Our experiment relies on applying the BM3D technique to a SAR image, alongside another traditional technique (Lee filter / frost filter in this case), followed by comparing them. SAR image samples are taken from the ASFData, from sentinel 1GRD dataset.

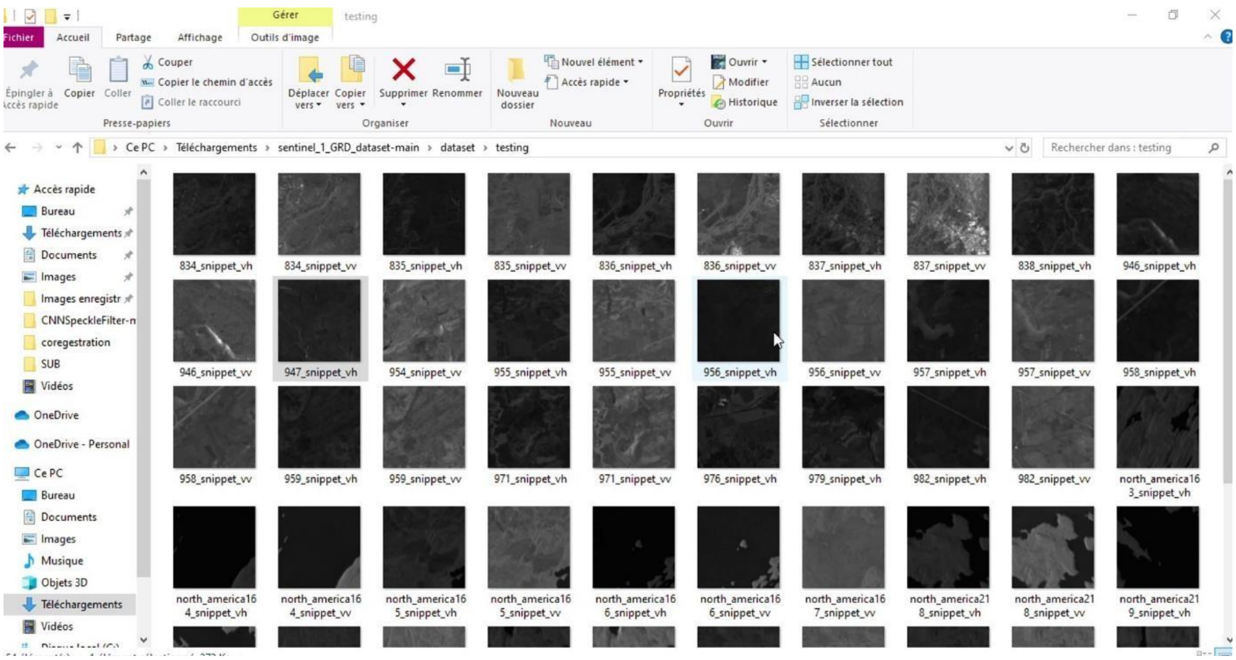



Figure 3.7: SAR image samples from Sentinel 1 GRD Dataset.

The ASF is a critical data center archiving and distributing synthetic aperture radar data collected through satellites. SAR data is relevant to a wide range of disciplines, including environmental monitoring, natural resource management, disaster response, and more.

When referring to "Alaska Satellite Facility data," typically in such a context, one refers to SAR data products and associated information, or metadata . The data run from radar images, derived products such as interferograms and polarimetric data, and other ancillary data.

ASF data is utilized by researchers, government agencies, and organizations in a host of applications, from the study of changes in the Earth's surface to the monitoring of ice and snow cover, terrain mapping, and evaluation of environmental hazards. [57]

Figure 3.8: ASF logo[75]

### 3.2) Proposed Method:

Speckle filtering is an indispensable step when dealing with applications involving images obtained by coherent systems, such as Synthetic Aperture Radar (SAR). Speckle is target-dependent phenomena. Therefore, estimating and reducing them requires identifying specific characteristics of image features, it is also one of the prominent topics in the SAR image processing research community, which initially addressed this issue using manually crafted feature-based filters. Even though classical algorithms gradually achieved better performance, convolutional neural networks (CNNs) have proven to be a promising alternative, given their superior capabilities in efficiently learning task-specific filters.

Free and open access to an extensive archive of SAR data is provided through the ASF website and data portal, making ASF an invaluable resource to the scientific community

Speckle noise is a common issue in synthetic aperture radar (SAR) imagery, degrading image quality and making interpretation difficult. The dataset used in this study includes synthetic speckle noise added to clean images to create a robust training set for the neural network.

The dataset is divided into training, validation, and testing sets, with sizes of 2000, 600, and 37 images respectively.

The proposed method involves a Convolutional Neural Network (CNN) designed to filter speckle noise from SAR images. The network architecture consists of a structure with multiple convolutional layers,

The model will be trained on a set of images selected from the database.

```
def __build_model(self, input_shape):
    model = Sequential([
            # encoder network
            Conv2D(32, 3, activation='relu', padding='same', input_shape=(28, 28, 1)),
            MaxPooling2D(2, padding='same'),
            Conv2D(16, 3, activation='relu', padding='same'),
            MaxPooling2D(2, padding='same'),
            # decoder network
            Conv2D(16, 3, activation='relu', padding='same'),
            UpSampling2D(2),
            Conv2D(32, 3, activation='relu', padding='same'),
            UpSampling2D(2),
            # output layer
            Conv2D(1, 3, activation='sigmoid', padding='same')
```

Figure 3.9: configuration of the model on the Dataset.

Input Layer:

- Conv2D (32, 3): A 2D convolutional layer with 32 filters, each of size 3x3.
- Activation: The ReLU activation function is applied.
- Padding: 'same' padding means the output size will be the same as the input size.
- Input Shape: The input shape is (28, 28, 1), which means the model expects grayscale images of size 28x28.

Max Pooling Layer:

- MaxPooling2D (2): A 2x2 pooling operation that reduces the spatial dimensions (height and width) of the feature maps by half.
- Padding: 'same' ensures the size of the output feature map is the same after pooling, which is not common for max pooling.

Second Conv2D Layer (Encoder):

- Conv2D (16, 3): A convolutional layer with 16 filters and a 3x3 kernel size.
- Activation: ReLU activation is applied.
- Padding: Again, 'same' padding is used.

Second Max Pooling Layer:

This further downsamples the spatial dimensions using a 2x2 pooling operation with 'same' padding.

Third Conv2D Layer :

- Conv2D (16, 3): Another convolutional layer with 16 filters and 3x3 kernel size in the decoder part.
- Activation: ReLU activation.
- Padding: 'same' padding ensures the feature map dimensions are preserved.

UpSampling Layer:

- UpSampling2D (2): This layer upsamples the feature map by a factor of 2, essentially reversing the max pooling downsampling.

Fourth Conv2D Layer:

- Conv2D(32, 3): This convolutional layer mirrors the first layer with 32 filters
- Activation: ReLU activation.
- Padding: 'same' padding is applied.

Second UpSampling Layer

This upsamples the feature maps again by a factor of 2, reversing the previous max pooling.

Final Conv2D Layer (Output):

Conv2D (1, 3): A final convolutional layer with 1 filter (since the output is expected to be a single channel).Activation: The sigmoid activation function is used, which is typical for binary or grayscale image output (values between 0 and 1).Padding: 'same' padding ensures the output has the same spatial dimensions as the input.

## 3.3) Evaluation metrics:

The following metrics, PSNR and SSIM, play essential roles in evaluating the fidelity and perceptual quality of images in various applications, helping to quantify the effectiveness of image processing algorithms and techniques.

### 3.3.1) PSNR (Peak Signal-to-Noise Ratio):

PSNR is a metric used to measure the quality of an image or video reconstruction. It compares the quality of a reconstructed image to that of a reference image by calculating the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. The higher the PSNR, typically expressed in decibels (dB), the better the quality of the reconstructed image. PSNR is widely used in image processing and video compression applications to assess the distortion introduced during encoding and decoding processes.

$$\boxed{\text{PSNR} = 10log10\ \left(\frac{R^2}{MSE}\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(3.1)}$$

- R is the maximum possible pixel value of the image (for an 8-bit image, R=255R = 255R=255).
- MSE stands for Mean Squared Error, which is calculated as:

$$\boxed{\text{MSE} = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(I(i,j) - K(i,j))^{2} \ldots\ldots\ldots (3.2)}$$

Where:

- MMM and NNN are the dimensions of the image (height and width).
- I(i,j)I(i, j)I(i,j) is the pixel value at position (i,j)(i, j)(i,j) in the original image.
- K(i,j)K(i, j)K(i,j) is the pixel value at position (i,j)(i, j)(i,j) in the compressed or reconstructed image.[58]

### 3.3.2) SSIM (Structural Similarity Index):

SSIM is a perceptual metric that quantifies the similarity between two images. Unlike PSNR, which only considers pixel-wise differences, SSIM takes into account the structural information of images, including luminance, contrast, and structure. It measures how well the perceived structural similarity of the two images matches the ground truth. SSIM values range from -1 to 1, where 1 indicates perfect similarity between the images. SSIM is widely used in image quality assessment tasks, including image restoration, compression, and super-resolution, where preserving perceptual quality is crucial.

$$\boxed{\text{SSIM (x, y)} = \frac{\mathbf{2\mu x\mu y+C1)(2\sigma xy+C2)}}{(\mu x2+\mu y2+C1)(\sigma x2+\sigma y2+C2)} \ldots\ldots\ldots\ldots\ldots (3.3)}$$

Where:

- x and y are the original and distorted images, respectively.

- $\mu x$ and $\mu y$ are the mean values of x and y, respectively.
- $\sigma x^2$ And $\sigma y^2$ are the variances of xxx and y, respectively.
- $\sigma xy$ is the covariance of x and y.
- C1and C2are small constants to avoid division by zero and to stabilize the calculation. These constants are typically set as:
    - C1= $(k1\ L)^2$
    - C2= $(k1\ L)^2$

where L is the dynamic range of the pixel values (e.g., L=255L = 255L=255 for 8-bit images), and k1 and k2 are small constants (often k1=0.01k_1 = 0.01k1=0.01 and k2=0.03k_2 = 0.03k2=0.03). [59]

## 4/ Results:

### 4.1) visual comparison of the results:

The following images show the visual comparison between the proposed method and the traditional ones (lee filter and frost filter) for three images from the dataset , a, b and c:

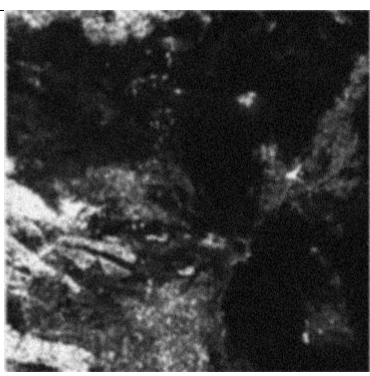
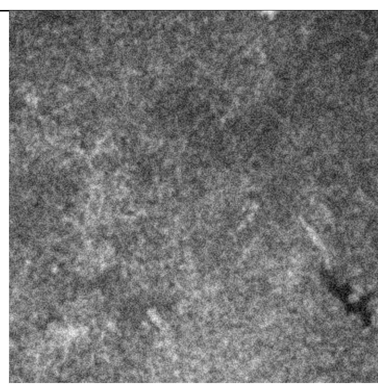
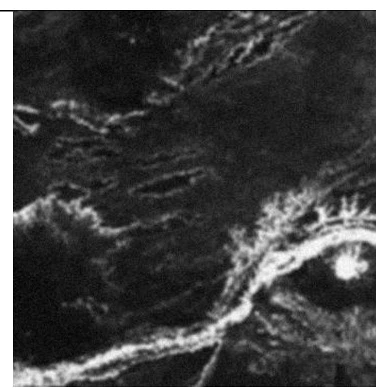
| Image a | Image b | Image c |
| --- | --- | --- |
|  |  |  |

Table 3.1 : images a,b,c with speckle .

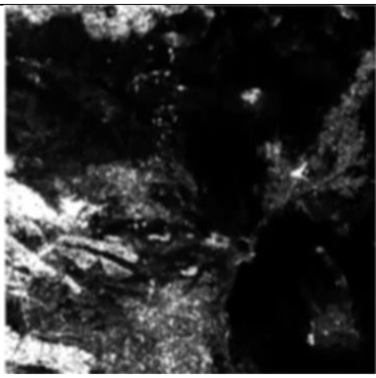
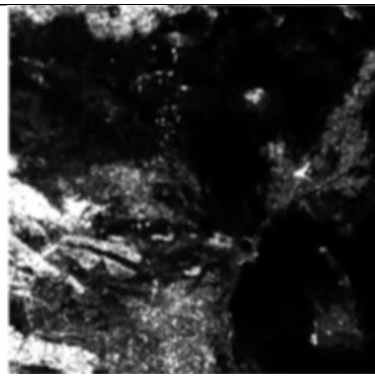
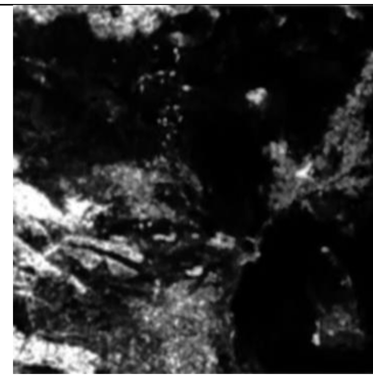
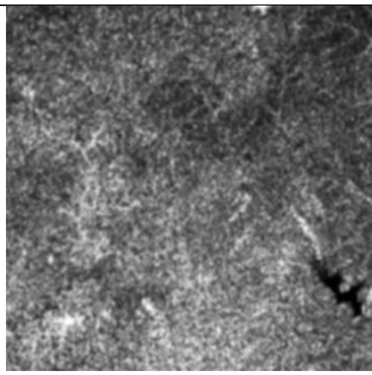
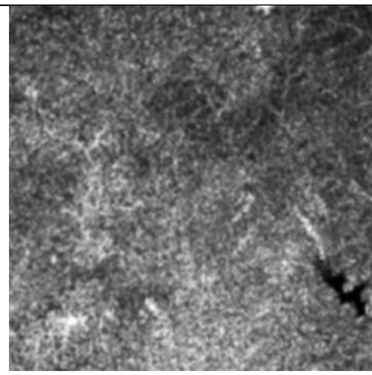
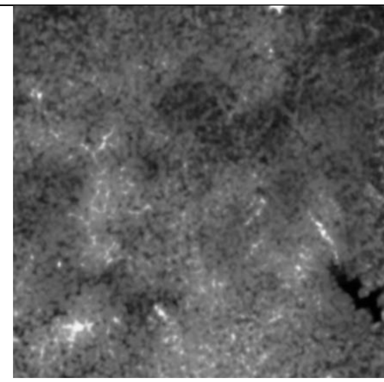
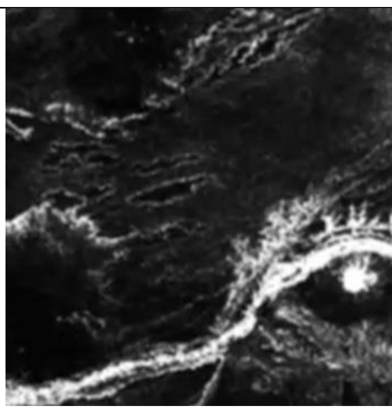
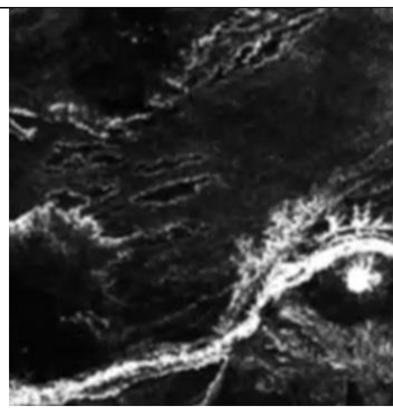
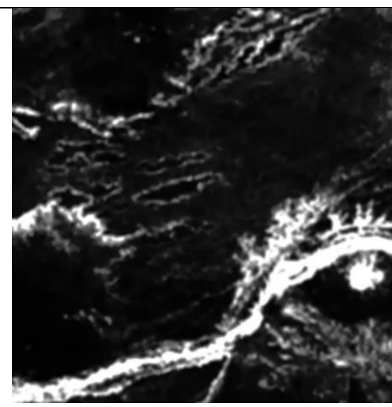
| Lee Filter | Frost Filter | BM3D |
| --- | --- | --- |
|  |  |  |
|  |  |  |
|  |  |  |

Table 3.2: SAR image results after filtering.

The BM3D method shows significantly better despeckling performance compared to traditional filters like Lee and Frost. Visually, BM3D effectively suppresses speckle noise while preserving fine details and sharp edges, resulting in clearer and more accurate images. In contrast, Lee and Frost filters leave behind residual speckle noise and tend to over-smooth the image, causing a loss of detail and blurring of edges.

**4.2) Quantitative results:**

Image a:

| Used Technique | PSNR | SSIM |
|---|---|---|
| **Lee filter** | 9,255109 | 0.135836 |
| **Frost filter** | 3.559860 | 0.145117 |
| **BM3D** | 8.600294 | 0.117395 |

Table 3.3: PSNR and SSIM for image a.

Image b:

| Used Technique | PSNR | SSIM |
|---|---|---|
| **Lee filter** | 17.264902 | 0.598403 |
| **Frost filter** | 17.823488 | 0.617461 |
| **BM3D** | 15.977160 | 0.553367 |

Table 3.4: PSNR and SSIM for image b.

Image c:

| Used Technique | PSNR | SSIM |
|---|---|---|
| **Lee filter** | 19.357145 | 0.860362 |
| **Frost filter** | 19.039116 | 0.857694 |
| **BM3D** | 18.704242 | 0.840749 |

Table 3.5: PSNR and SSIM for image c.

## 4.3) Evaluation of performance:

### 4.3.1) PSNR comparison:

Lee Filter and Frost Filter both show relatively higher PSNR values compared to BM3D .PSNR measures the ratio between the maximum possible signal and the noise suppression.

The BM3D method shows significantly better despeckling performance compared to traditional filters like Lee and Frost. Visually, BM3D effectively suppresses speckle noise while preserving fine details and sharp edges, resulting in clearer and more accurate images. In contrast, Lee and Frost filters leave behind residual speckle noise and tend to over-smooth the image, causing a loss of detail and blurring of edges.

### 4.3.2) SSIM comparison:

When comparing SSIM, which evaluates the perceptual quality of the images in terms of structure, luminance, and contrast, the Frost filter achieves the highest score, followed by the Lee filter , with BM3D scoring the lowest. SSIM is particularly sensitive to changes in texture and structure, which explains BM3D's lower SSIM, as it emphasizes preserving fine details and avoiding over-smoothing, which might be perceived as structural noise. In contrast, the Frost and Lee filters, although smoothing more aggressively, might retain more global structure in the image, leading to slightly higher SSIM values.

## 5/ Conclusion :

In this chapter, we evaluated the performance of our proposed despeckling algorithm in comparison to traditional filters like Lee and Frost using both qualitative and quantitative metrics.

Our results demonstrate that while traditional filters achieve higher PSNR and SSIM values, indicating effective noise reduction and structural preservation, they often fall short in maintaining fine details and textures. The BM3D method, despite having slightly lower PSNR and SSIM, excels in preserving intricate details and avoiding excessive smoothing, which results in visually superior images. This balance between noise reduction and detail preservation highlights BM3D's effectiveness, making it a robust choice for despeckling SAR images where image clarity and fidelity are critical. Ultimately, the choice of despeckling method should consider both quantitative metrics and visual quality to achieve the best overall performance for specific applications.

## General conclusion:

In this thesis, we have explored the complexities of SAR imaging and speckle noise, developed an understanding of deep learning and convolutional neural network (CNN) architectures, and implemented an advanced despeckling method to address these challenges.

Chapter 1 provided a foundational overview of SAR imaging and the inherent speckle noise phenomenon, setting the stage for understanding the impact of noise on image quality and the need for effective despeckling techniques.

Chapter 2 delved into deep learning methodologies, particularly CNN architectures, highlighting their potential for image processing tasks. We discussed various architectures and their strengths, establishing a basis for selecting an appropriate model for SAR image despeckling.

Chapter 3 presented the implementation of our proposed despeckling method, which leverages advanced deep learning techniques to improve SAR image quality. Through rigorous evaluation, including comparisons with traditional filters and detailed analysis using metrics like PSNR and SSIM, we demonstrated the effectiveness of our approach.

Overall, this thesis underscores the importance of integrating cutting-edge deep learning techniques with traditional image processing methods to achieve superior performance in SAR image despeckling. Our findings highlight the trade-offs between different methods and the necessity of balancing quantitative metrics with perceptual image quality to enhance the utility and accuracy of SAR imagery.

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