Breast cancer is a critical health challenge for women worldwide. Although standard X-ray mammography is the gold standard for screening, it presents limitations, including the use of ionizing radiation, breast compression, and reduced sensitivity in dense breasts. Microwave Imaging has emerged as a highly promising, non-ionizing, and pain-free alternative, which leverages the high contrast in dielectric properties between cancerous and healthy tissues. A further advancement is represented by quantitative microwave imaging, that aims to provide a map of the dielectric properties of breast tissues, enabling their anatomical and functional characterization while overcoming the limitations of standard qualitative methods. Despite the high contrast between the dielectric properties of cancerous and fat tissues, fibroglandular tissue acts as a confounding factor because of the lower contrast between its and cancer dielectric properties. As a consequence, breast density assessment plays a crucial role in imaging interpretation and cancer risk evaluation. Deep Learning algorithms have recently shown great promise in automating breast density classification, providing an objective tool that can significantly enhance diagnostic workflows.

The primary motivation of this doctoral thesis was to advance the microwave imaging technology toward a quantitative imaging modality. This has been done in particular with reference to the MammoWave device (UBT Srl, Perugia, Italy). First, the safety of the used device was assessment through a comprehensive dosimetric study based on a simulation platform to estimate temperature increases induced in breast tissues by an exam. Temperature increases were estimated based on SAR distributions on five distinct digital breast models, taking into account the different configurations and frequencies at which the device operates. The highest temperature increase obtained in the analysis is lower than 60 μK (peak localized in fibroglandular tissue or skin, depending on the radiation frequency and breast density), assuring the patient's safety during the breast examination.

The MammoWave device was then used as a test reference for an implementation of the Contrast Source Inversion (CSI) method. Initially tested on simple virtual phantoms to verify the capability of the method to map inclusion with various contrasts and diameters, the method was further developed with advanced variants. Through the application of the method to the reconstruction of digital breasts, the critical importance of an informed initial guess was observed. Experimental data from cylindrical phantoms were then used, integrating a dedicated system calibration procedure that guaranteed a good congruence between experimental scattered fields and numerical simulations for the same target. Experimental phantom reconstructions confirmed accurate inclusion localization and background matching. Frequency analysis revealed a trade-off: while higher frequencies improve spatial resolution, the noisy conductivity maps are recovered above 5 GHz. Finally, the application of the CSI with segmentation constraint yielded permittivity values more reliable than those obtained with standard CSI, and final reconstructed maps independent of the choice of the initial guess.

The study of the imaging method highlighted the critical role of *a priori* information, such as target shape, and averaged electric properties, which are directly correlated to breast density.

Consequently, this research proposes a Deep Learning-based approach for automatic breast density classification, leveraging the extensive repository of MWI data from the ongoing MammoWave trials.

A custom Convolutional Neural Network was developed to classify patients’ breasts as dense or non-dense using 6709 raw measurement data collected from multiple clinical sites, with labeling from radiologists' BI-RADS assessments. The classifier achieved a total accuracy of 80.1 % ± 0.7 % on the test set, with 79.4 % ± 1.8 % and 80.8 % ± 2.4 % accuracy for low- and high-density cases, respectively. Furthermore, bilateral consistency was identified as a key indicator of classification reliability, reaching 84 % of performance accuracy when verified, demonstrating that it is possible to aid clinical decision-making in screening programs with quantitative results based on non-ionizing radiation.