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# Machine learning for sign language recognition: Application on smart buildings

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## Abstract

Recent advances in mobile computing, wireless sensing and communication technologies, consumer electronics have modernized our cities and living environments. Buildings, roads, and vehicles are now empowered with a variety of smart sensors and objects that are interconnected via machine-to-machine communication protocols, accessible via the Internet, to form what is known as the Internet of Things (IoT). The power of IoT expands when coupled with Machine Learning, since the later offer techniques that allow analyzing the vast amount of data generated by sensors and actuators. Smart buildings are an appealing example of IoT and machine learning applications offering higher energy saving and occupants satisfaction through dynamic control.

Vocal virtual assistants (e.g., Amazon Alexa, Google Home) are now a central component of the smart house. However, they are not adapted to deaf and mute people who communicate using sign language. Efficient alternative communication means inside the house are required to assist the interaction of deaf and hearing-impaired people.

The main goal of this thesis is to conceive and realize a solution based on machine learning for sign language recognition that allows the control of a smart home environment through gestures.

**Keywords:** Smart buildings, Machine learning, Sign language, Disabled people, Human-Computer interaction.

## Résumé

Les progrès récents dans l'informatique mobile, la détection sans fil et les technologies de communication, l'électronique grand public ont modernisé nos villes et nos milieux de vie. Les bâtiments, les routes et les véhicules sont désormais dotés de divers capteurs et objets intelligents interconnectés par des protocoles de communication machine à machine, accessibles via Internet, pour former ce qu'on appelle l'Internet des objets (IoT). La puissance de l'IoT se développe lorsqu'il est couplé avec le Machine Learning, puisque ce dernier offre des techniques qui permettent d'analyser la grande quantité de données générées par les capteurs et les actionneurs. Les bâtiments intelligents sont un exemple attrayant d'applications d'IoT et d'apprentissage automatique offrant des économies d'énergie plus élevées et la satisfaction des occupants grâce au contrôle dynamique.

Les assistants vocaux virtuels (par exemple, Amazon Alexa, Google Home) sont désormais une composante centrale de la maison intelligente. Cependant, ils ne sont pas adaptés aux personnes sourdes et muettes qui communiquent en langage gestuel. Des moyens de communication alternatifs efficaces à l'intérieur de la maison sont nécessaires pour faciliter l'interaction des personnes sourdes et malentendantes.

L'objectif principal de cette thèse est de concevoir et de réaliser une solution basée sur l'apprentissage automatique pour la reconnaissance du langage des signes qui permet le contrôle d'un environnement domestique intelligent à travers des gestes.

**Mots clés:** Bâtiments intelligents, apprentissage automatique, langue des signes, personnes handicapées, interaction homme-machine.

# ملخص

لقد حدث التطور الأخير في مجال الحوسبة المتنقلة والاستشعار اللاسلكي وتقنيات الاتصال، والإلكترونيات الاستهلاكية مدننا وببيئتنا المعيشية. أصبحت المباني والطرق والمركبات الآن مزودة بمجموعة متنوعة من المستشعرات والأجسام الذكية المتصلة ببعضها عبر بروتوكولات الاتصال من جهاز إلى جهاز، والتي يمكن الوصول إليها عبر الإنترنت، لتكوين ما يُعرف بإنترنت الأشياء. تتوسع قوة إنترنت الأشياء عند اقترانها بتعلم الآلة، حيث إن أحدث تقنيات تتيح تحليل كمية كبيرة من البيانات التي تولدها أجهزة الاستشعار والمشغلات. تُعد المباني الذكية مثالاً جذاباً على تطبيقات إنترنت الأشياء وتعلم الآلة التي توفر طاقة أعلى ورضا راكبي السيارة من خلال التحكم الديناميكي.

أصبح المساعدون الافتراضيين الصالح (على سبيل المثال، Amazon Alexa و Google Home) الآن مكوناً أساسياً في المنزل الذكي. ومع ذلك، فإنها غير مكيفة مع الصم وكتم الأشخاص الذين يتواصلون باستخدام لغة الإشارة. وسائل الاتصال البديلة الفعالة داخل المنزل مطلوبة للمساعدة في تفاعل الصم وضعاف السمع.

والهدف الرئيسي لهذه الفرضية هو تصور وتحقيق حل يستند إلى تعلم الآلة للتعرف على لغة الإشارات التي تسمح بالتحكم في بيئه منزلية ذكية من خلال الإيماءات.

**الكلمات المفتاحية:** المباني الذكية ، التعلم الآلي ، لغة الإشارة ، المعاقوون ، التفاعل بين الإنسان والحواسوب.

## Dedications

*I dedicate this thesis to my parents for whom a whole book of dedications would not be enough to express my gratitude to them. For all of their support, encouragement, love and sacrifices that have brought me to this point in my life and continue to keep me moving forward. May Allah preserve them as well as all moms and dads in the world.*

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