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## Computational intelligence & modeling of crop disease data in Africa

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# **Computational intelligence & modeling of crop disease data in Africa**

Godliver Owomugisha

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and in accordance with  
the decision by the College of Deans.

This thesis will be defended in public on

Friday 28 August 2020 at 16.15 hours

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