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Computational intelligence & modeling of crop disease data in Africa

Owomugisha, Godliver

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Computational intelligence & modeling of crop disease data in Africa

Godliver Owomugisha

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Africa**

PhD thesis

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on the authority of the
Rector Magnificus, Prof. C. Wijmenga
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

by

Godliver Owomugisha

born on 2 August 1987
in Bushenyi, Uganda

Supervisors

Prof. M. Biehl

Prof. N. Petkov

Co-supervisors

Dr. E. Mwebaze

Dr. J.A. Quinn

Assessment committee

Prof. D. Karastoyanova

Prof. L.C. Verbrugge

Prof. B. Hammer

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Groningen
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