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Mexican poppy (*Argemone mexicana*) control in cornfield using deep learning neural networks: a perspective

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ABSTRACT
Mexican poppy (*Argemone mexicana*) is a widespread noxious annual weed associated with crops such as corn (*Zea mays* L.), and this weed is persistent because it produces a seed bank. This invasive weed species must be controlled even in the dry season because Mexican poppy has a deep-reaching root system, which taps water from deep soil layers. Cases of a human death caused by Mexican poppy seeds in South Africa, India, and other Eastern countries were reported from the early years of the twentieth century. However, when weeds are controlled uniformly instead of site-specific or precision farming method across the spatially variable fields, there are environmental pollution challenges. Site-specific weed control techniques have gained interest in the precision farming community over the last years mainly because of Global Positioning System (GPS) applications, and a controlled measure of herbicides are applied where there are weeds in the field, and areas with more clusters of weeds receive the correct amount of herbicide application. Mexican poppy has prickles and is a nuisance to farmers, and herbicides represent a severe health hazard to humans due to chemical concentrations in water. For that reason, we propose the design of a site-specific weed control plan to use a row-guided robot to detect and identify weeds with accuracy, control speed timeously, and spray herbicides with a high level of precision and automation. These robotics methods are reported to be environmentally conscious, and economically efficient with less labour and management. The proposed method of deep learning neural networks, which use row-guided robots, a machine is trained on multiple images to identify weeds automatically from the main crop, and release a controlled measure of herbicides based on weed location and density, and spray weeds on-the-go upon emergence.

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Importance of a maize crop

Corn (Zea mays L.) is one of the major cereal crops in the world providing an estimated 15% of the world's protein and 20% of the world's calories (Nuss and Tanumihardjo 2010). Protein and caloric shortages in the large proportion of world population are resulting in reduced growth and development and increased disease, particularly among children (Pimentel et al. 1975). In Southern Africa region, corn contributes to nearly half of the total human caloric intake and is a preferred cereal compared to Rice and Wheat, which are preferred in other parts of the world (Ranum et al. 2014). In South Africa, corn is the staple food for the majority of the human population (Gouse et al. 2006), and for years in succession, South Africa remained in the top 10 of corn producing countries in the world (FAO 2008). At any time since 1995, there is approximately 3–4 million ha of agricultural land planted to commercial corn in South Africa, which is about 60–70% of the total area under field crop production (DAFF 2013). For this reason, corn qualifies as a chief crop in South Africa (Figures 1–3).

Mexican poppy weed

Excessive competition from weeds is a significant constraint in South African corn fields, reducing corn yield and farmer's income (Marava 2016). Weeds must be controlled even in the dry season, as some invasive weed species such as Mexican poppy (*Argemone mexicana*) have a deep-reaching root system, which taps water from deep soil layers (Steiner and Rockström 2003). *Argemone mexicana* is a widespread noxious annual weed associated with crops, and it is often persistent owing to its massive soil seed bank (Namkeleja et al. 2013). In addition, despite its ability to germinate and thrive in a wide range of climatic conditions, due to their immature embryos at the time of seed detachment from the parent plant, not all seeds in the soil bank are readily viable for

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Figure 1. Mexican poppy between rows of harvested corn field in Potchefstroom, South Africa (Photo credit; Grain Crop Institute of the Agricultural Research Council of South Africa).

germination. Thus, only about 20% the seeds will germinate while rest undergo morphological dormancy until their embryos are fully developed in the following seasons prompting a continuous build-up of the soil seed bank (van der Westhuizen and Mpedi 2011). *Argemone mexicana* is one of the prominent weeds of maize and sunflower in South Africa, (Henderson and Anderson 1966). Its first record in the country was reported in 1894 and it is largely pervasive to coastal areas of KwaZulu-Natal, the lowveld of Mpumalanga and Limpopo provinces (Henderson 2006).

In developing countries, *A. mexicana* is a health hazard because of its prickliness and nuisance to subsistence farmers who sometimes do not have proper protective clothing. *Argemone mexicana* is a prolific seed producer with a single plant capable of producing as much as 40,000 seeds most of which fall close to the parent plant. Nevertheless, the characteristic small size of the seeds facilitates its dispersal by water, or sticking to animals, machineries, and grains (Ampong-Nyarko and De Datta 1991). The seeds of this weed are often found in coarse grains used for pig feeds. The small, dark-brown to black seeds are like tiny peppercorns and contain a group of isoquinoline alkaloids and derivatives such as: protopine, berberine, chelerythrine, and sanguinarine (Fletcher et al. 1993).

Figure 2. Mexican poppy in harvested corn field in Mexico, North America (Photo credit: Anna Bruce/TheCultureTrip).

Figure 3. Mexican poppy in harvested corn field in Mexico, North America (Photo credit: Anna Bruce/TheCultureTrip).

Some weed seeds are highly poisonous and toxic and can cause severe illness and death while others are non-toxic but can interfere with digestion or severely lower nutrient intake, reducing growth (van Barneveld 1999). For example, seeds of *A. mexicana*, are extremely toxic to humans and poultry. The Mexican poppy is declared invasive weed 'category 1b' according to National Environmental Management: Biodiversity Act, 2004 (Act No. 10 of 2004) alien and invasive species lists, 2016, which prohibit any propagation and necessitate its immediate removal and eradication. The South African Department of Forestry and Fisheries (DAFF) because of its seeds that may represent a hazard to human or animal health when consumed (NDA 2001). In the past years, cases of human death caused by Mexican poppy seeds were reported in South Africa, India, and other Easter countries from as early years of the twentieth century (Meaker 1950; Steyn 1950; Botha and Penrith 2008). For example, between August and September 1998, over 3000 persons fell ill, and more than 65 died in the state of Delhi alone in India because of *Argemone mexicana* poisoning (Verma et al. 2001). Epidemic dropsy occurred in South Africa following the contamination of flour by *A. mexicana* (Sharma et al. 1999). Epidemic dropsy is caused by sanguinarine, an alkaloid constituent of several plants, including the Mexican poppy, *A. mexicana* (Aronson 2014). Epidemic dropsy, is characterised by the pathological accumulation of diluted lymph in body tissues and cavities (Verma et al. 2001).

Mexican poppy and livestock

Apart from making it to the list of dangerous nuisances in Australia, this toxic agricultural weed was reported to be poisonous to livestock (Bailey 1897). In Southern Africa region, *Argemone mexicana* is considered as a poisonous plant affecting livestock (Botha and Penrith 2008). Ground Mexican poppy *(A. mexicana)* seed produced growth depression, oedema and death when fed at 1% and 3% of a basal ration to day-old, layer strain, cockerel chickens (Norton and O'Rourke 1980). This noxious weed is listed in the international poisonous plants checklist as one of the most dangerous weeds around the world (Kaplan 2008).

Environmental pollution

Challenges in weed management include the occurrence of multiple weed species in the field, variable emergence among weed species, different spatial distribution and weed densities, which lead to the persistence of weed patches (Ndou 2009). The overuse of synthetic agro-chemicals for pest and weed control has increased environmental pollution, unsafe agricultural products, and human health concerns (Khanh et al. 2005). The International Survey of Herbicide-Resistant Weeds (www.weedscience.org) reports 388 unique cases (species x site of action) of herbicide-resistant weeds globally, with 210 species (Heap 2014). Due to adaptation and resistance developed by weeds to chemicals, every year higher amounts and new chemical compounds are used to protect crops, causing undesired side effects and raising the costs of food production (Carvalho 2006). As a consequence, persistent residues of these chemicals contaminate food and disperse in the environment. During a panel discussion organised by Bayer, Stephen Powles, director of the Australian Herbicide Resistance Initiative reported that indeed weed resistance is a massive problem that's threatening the world's food supply (Bayer News 2017).

Spatial distribution and site-specific weed management

Brown et al. (1994) reported that weeds are distributed unevenly within agricultural fields. Roham et al. (2014) physically assessed weed growth in a farming system. The results of the author's assessment indicated that these weeds occur in patches. However, spatial maps of the farm showed that size and structure of those patches differed within a farm. Therefore, a logical method of weed control in this kind of a situation would be to correctly apply the correct amount of a correct herbicide, at a correct time and location. Researchers projected that by adjusting the number of herbicides used based on weed density and spraying weeds only where weeds occur in the field may be financially and environmentally beneficial as opposed to spraying the entire area uniformly (Heisel et al. 1997; Wagner 2004; Martín et al. 2015).

Despite researchers realising that weeds occurrence in agricultural fields is non-uniform, it was only in the previous decade that the in-field spatial distribution of weeds has received detailed attention (Rew and Cousens 2001). Site-specific weed control techniques have gained interest in the precision farming community over the last years mainly because of GPS applications and associated site-specific management applications (Weis et al. 2008). Site-specific weed management means applying control measures only where weeds are located at densities more significant than those that cause no economic losses (Shaw 2005). In a study conducted in Denmark, Heisel et al. (1999) indicated that suitable herbicides spraying technology and support systems of site-specific management could potentially reduce herbicides application by 30%–70%. That is because, in site-specific weed control, herbicides are applied where there are weeds in the field, and areas with more clusters of weeds receive the correct amount of herbicide application.

When herbicides are applied uniformly, only a low percentage reaches targeted weeds, and a large proportion is lost into the environment because of drift or evaporation (Christensen et al. 2009). For this reason, it is indisputable that the use of herbicides in agricultural farming system must be strategically reduced to protect the environmental quality (Pimentel et al. 1991; Søgaard 2005).

Approaches to site-specific weed management

In the past decade, counting and surveying of weeds for herbicide application were done with time-consuming manual surveying, although various mechanical and automated systems of weed identification and mapping were proposed (Manh et al. 2001). Manual surveying may not be practical in an intensive commercial farming system where profit is a goal, and customer demands must be met with both quantity and quality of fresh produce. A few years later, weed maps were created using continuous sampling that has either relied on human vision or remotely sensed imagery (Barroso et al. 2005). An observer, logging weed occurrence from a tractor, or a four-wheel motorcycle equipped with a differential GPS and data logger produces weed maps (Rew and Cousens 2001). This system generated excellent maps. However, the method was labour-intensive for practical situations.

Based on studies conducted by Naeem et al. (2007) and Siddiqi et al. (2009), a high spatial resolution, real-time weed infestation detection system could be the ultimate solution for site-specific weed management. For a row-guided robot to detect and identify weeds with accuracy, control speed timeously, and spray herbicides with a high level of precision and automation, there is a need for effective weed control method that is environmentally safe, and economically efficient with less labour and management.

Looking forward

Recent advances in machine learning yielded new techniques to train deep neural networks (Kooi et al. 2017), which has a potential to successfully recognise patterns of objects such as weeds by leaf morphological structure and differentiate weeds from the main crop. Deep learning refers to a branch of machine learning that train neural network architectures that are made of numerous nonlinear processing layers (Grinblat et al. 2016). This system uses forward propagation, which is a neural network way of classifying a set of images. A neural network is an essential tool for recognition and classification of images (Lin et al. 2007 and Kiranyaz et al. 2008). Deep networks use edges to detect different parts of the image to be identified, i.e. Mexican poppy that has a unique leaf morphological structure.

Convolutional neural networks have received much attention in recent years, and these neural networks have proven capable of outperforming previous records in image recognition challenges (Dyrmann et al. 2016). Deep neural network system requires a broad set of image data. These large set of data is trained for pattern complexity and to improve accuracy in classifying images of weeds as early as few days after corn emergence. According to Dyrmann et al. (2016), this method of the convolutional neural network is less affected by natural variations such as changes in illumination, shadows, skewed leaves, and occluded plants as compared to other previous image classification methods.

When weeds are adequately controlled at an early crop growth stage, corn can potentially establish well on the soil with less competition for nutrients and other resources, consequently improving yields for farmers. The deep neural network system takes much longer time to train data even on a faster Central Processing Unit (CPU), and therefore, deep learning neural networks need high-performance training Graphics Processing Unit (GPU) to finish work quickly. In our project that seek to produce a row-guided robot for site-specific weed management, we intend to use of deep learning neural networks method to automatically identify weeds from main corn crop for effective and efficient control of Mexican poppy on-the-go upon emergence.

Disclosure statement

No potential conflict of interest was reported by the authors.

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Prof. Matshwene E. Moshia III (Edwin) is a Specialist Researcher in Soil Information System at the Institute for Soil, Climate, and Water of the Agricultural Research Council (ARCISCW) in South Africa. He received a Fulbright Scholarship and obtained a Ph.D. degree in Soil Sciences specialising in Precision Agriculture at Colorado State University, USA. His Soil Science fields of specialisation cover Pedometrics, Precision Agriculture, and Environmental Soil Sciences with a specific focus on Manure Management and the Environment. He has received awards from notable organisations such as Soil Science Society of America (Div. S04 and S08), Western Soil Science Society of America, International Society of Precision Agriculture, Foundation of Agronomic Research, Regional Universities Forum for Capacity Building in Agriculture (RUFORUM), Forum for Agricultural Research in Africa (FARA), and was awarded African Young Professional in Science. In 2016, he received another Fulbright Scholarship and went to the University of Florida in the USA as a Fulbright Research Scholar in Precision Agriculture working on deep learning neural networks. He is a member of Gamma Sigma Delta since 2006, and a rated researcher (2016-2021) with National Research Foundation (NRF) of South Africa. This six-year (2016-2021) recognition award is given to scholars with a sustained recent record of productivity in their field and is recognised by their peers as having produced a body of quality work. Moshia has been appointed to serve on FAOIntergovernmental Technical Panel on Soils (FAO-ITPS). He is also an Editorial Board Member of quite a number of Scientific Journals in his field.

Dr Solomon W. Newete is a Senior Researcher at the Agricultural Research Council-Institute for Soil, Climate and Water (ARC-ISCW) with a research interest in Invasive alien weeds, biological control of alien weeds, environmental pollution, and remote sensing. He holds a Ph.D. degree in Environmental Sciences and an M.Sc. in Resource Conservation Biology from the University of the Witwatersrand (Wits) and a B.Sc. degree (4 years) in Agriculture from the University of Asmara, Eritrea. Dr Newete was employed as a post-doctoral researcher at the University of Witwatersrand (Wits) for two and a half years before he moved to the current position as Senior Researcher at ARC-ISCW. Dr Newete has been involved in the supervision of more than 20 postgraduate research projects. He has also worked as lead investigator and collaborator in a number of other research projects among which are (i) 'Life in City' (mapping the ecosystem services and disservices of alien street trees in the city of Johannesburg (funded by Wits School of Governance), (ii) Bush Encroachment funded by the Department of Environmental Affairs (DEA), (iii) Tamarix NRF project (funded by the National Research Fund of South Africa), and (iv) the sediment sources identification and erosion control measures in China and South Africa watersheds project (jointly funded by the National Natural Science Foundation of China (NSFC)/NRF. His previous work experience includes Co-lecturer at Wits University, educator and principal (High School) and Agricultural Extension Service Expert, among others. He has published several articles in international peer-reviewed ISI rated journals and accumulated considerable experience in his field of expertise.

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